



EDITOR
ASSOC. PROF. DR. TEFİDE KIZILDENİZ GÜRBÜZ

**ARTIFICIAL INTELLIGENCE,
SMART TECHNOLOGIES AND CLIMATE
CHALLENGES IN MODERN AGRICULTURE**



BZT TURAN

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ASSOC. PROF. DR. TEFİDE KIZILDENİZ GÜRBÜZ



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She has actively participated in numerous national and international research projects funded by organizations such as the European Union, FAO-related programs, and TÜBİTAK. Her interdisciplinary work spans climate resilience, food security, and sustainable agricultural systems, including contributions to projects addressing agricultural adaptation strategies in fragile and conflict-affected regions. In addition, she has led innovative research initiatives such as the development of aeroponic systems for disease-free plant production.

Dr. Gürbüz has authored and co-authored multiple peer-reviewed publications in high-impact international journals, including studies on climate change effects on crop growth, AI-based agricultural applications, and postharvest technologies. Through her teaching, research, and international collaborations, Dr. Gürbüz continues to contribute to advancing climate-resilient and technology-driven agricultural systems. She also supervises graduate students working on climate modeling, crop simulation, and digital agriculture topics, contributing to the development of next-generation researchers in the field.



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Preface

The combination of technical innovation, environmental concerns, and the pressing need for sustainable food production methods is causing a major change in agriculture. Artificial intelligence, data integration, and smart technologies are all moving quickly, and they are changing the way we monitor, manage, and improve agricultural systems. At the same time, problems throughout the world like climate change, lack of resources, and new food safety hazards need answers that are both comprehensive and look to the future.

Smart and Sustainable Agriculture that includes AI, Data Integration, and Climate-Driven Challenges is a book that pulls together essays from several fields that show how contemporary agriculture is changing. The chapters in this book show how new technology, such data fusion methods that combine satellite, UAV, and sensor data, and artificial intelligence-driven synthetic data synthesis, might help farmers make better decisions.

In addition to digital advancements, the book talks about important technical issues in agricultural systems, such how to make contemporary equipment more fuel-efficient, reduce emissions, and keep noise levels down, with a focus on how these issues affect the environment. It also looks at important problems that come up when climate change, plant health, and food safety all come together. For example, it talks about the expanding hazards presented by mycotoxins and what they mean for food systems throughout the world from a One Health point of view.

This book tries to provide a full picture of the problems and chances that modern agriculture faces by bringing together ideas from agricultural engineering, data science, environmental sciences, and food safety. Researchers, practitioners, policymakers, and students who want to understand the intricacies of sustainable and technology-driven agricultural systems should use it.

The editor wants to thank all of the writers who contributed for their hard work and devotion. We hope that this book will be a helpful resource and motivate further study and new ideas that will lead to agricultural systems that are more resilient, efficient, and sustainable.

Assoc. Prof. Dr. Tefide KIZILDENİZ GÜRBÜZ

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CHAPTER 1

Climate Change, Plant Health, and Food Safety: A One Health Perspective

Ahmad IQBAL¹

Tefide KIZILDENİZ²

Abstract

Climate change is a major threat to agricultural productivity, plant health, and global food safety. High temperatures, irregular patterns of precipitation and severe weather occurrences negatively affect crop growth and physiological status. These environmental disturbances also influence the persistence, demography, and distribution of phytopathogens and pests, leading to increased incidence and severity of plant diseases. Plant diseases also pose significant risks to food safety. Fungal pathogens attack a wide variety of staple crops and produce mycotoxins, such as aflatoxins and fumonisins, which can remain in food and feed even after processing. These toxins have long-term adverse effects on human and animal health. Moreover, diseased plant tissues can serve as reservoirs for human pathogenic bacteria, increasing contamination risks in fresh fruits, vegetables, and cereals. The links between climate change, plant health, and food safety highlight the need for a One Health approach. Enhancing food system resilience requires integrated and adaptive management strategies.

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Yield losses can be minimized by creating climate-resilient crop cultivars with abiotic stress tolerance and disease resistance. Improved agronomic practices combined with integrated pest and disease management suppress pathogen proliferation. Strong postharvest handling and storage reduce fungal growth and mycotoxin production, while monitoring systems and early-warning technologies facilitate risk mitigation.

Keywords: Climate Threat, Plant diseases, Mycotoxins, Food safety, One Health, Crop resilience

1. Introduction

Climate change is a topical international issue that undermines agricultural sustainability, plant health, and food safety. Raised temperatures, altered rainfall patterns, and increased occurrence of severe weather are changing agro-ecosystems globally. The annual average global surface temperature has already risen by around 1.1°C relative to pre-industrial levels, and further warming is expected over the 21st century (Wang et al., 2018). These climatic changes control the physiology of crops, pathogen development and microbial viability in agriculture. Climate change, therefore presents substantial threats to food production and also to the security of the food supply.

The health of plants is one of the key determinants of food security in the world. Almost 80% of the food that people consume is produced by crops, but plant pests and diseases cause significant losses in production each year. It has been estimated that annual losses are up to 40% of the overall crop yields in the world because of plant pests and diseases, which cost the global economies USD 220 billion or more per year (IPPC, 2023). It is projected that climate change will increase such losses. Alterations in temperature and humidity are also capable of changing the distribution and life cycle of plant pathogens and insect pests. Warmer climates tend to have a faster development of pests and they have more generations in a season. Moreover, the warmer winters allow the pests to live in areas where their numbers were limited by the cold temperatures (Skendžić et al., 2021).

There is an effect of environmental changes on the growth and spread of invasive plant pathogens. Several studies indicate that several fungal and bacterial pathogens are changing their geographic patterns to higher latitudes and altitudes with increasing temperatures (Salazar-Hamm and Torres-Cruz, 2024). Such changes in ranges can expose new agricultural areas on farms to new illnesses. Climatic stress may also disrupt defense systems in plants, contributing to the increased vulnerability of crops to infection and infestation

(Singh et al., 2023) These effects may reduce the yield of crops, reduce food quality and augment dependence on chemical management methods.

There are also direct implications of climate change to food safety. The environmental factors have a powerful effect on the growth of foodborne pathogens and fungi that produce toxins. Humidity and high temperature provide good environment to the growth of mycotoxin producing fungi including *Aspergillus* and *Fusarium* species. The fungi produce mycotoxins such as aflatoxins and fumonisins which are harmful to humans and animals (Alam et al., 2022). According to climate forecasts, the threat of aflatoxin contamination of various crop-producing areas might increase due to the warming and drought conditions (Kubik et al., 2023). In addition, extreme weather conditions like floods and storms may pollute crops and irrigation water with pathogenic microorganisms thus exposing more people to the risk of outbreaks of food borne diseases (Duchenne-Moutien and Neetoo, 2021).

The One Health approach has a good framework of understanding such interrelated challenges. One Health acknowledges the strong interrelations between the health of human beings, animals, plants and ecosystems. In such a context, plant health is a very important though often underestimated element. The healthy plants ensure safe and healthy food systems and reduce the risk of transmitting pathogens through the environment and agricultural interfaces (Rizzo et al., 2021). Climate change also highlights the need to take interdisciplinary approaches since environmental disruptions also have impacts that are complementary on crop health, microbial ecology, and food safety hazards.

Recent study highlights the interaction of climate change and antimicrobial resistance (AMR) in food systems. Ecological and climatic conditions affect the survival of microorganisms and allow horizontal gene transfer in the soil and water. The processes can help to spread resistant microorganisms between plants, animals, and humans (Woh et al., 2025). Therefore, synergistic surveillance and risk evaluation plans are essential in order to control the emerging hazards to food security even in climatically unstable circumstances.

The interplay between climate change, plant health, and food safety is thus a complex concept that requires a detailed understanding in order to come up with resilient agricultural systems. One Health views interdisciplinary cooperation between the disciplines of plant pathology, environmental science, veterinary medicine, and public health. Climate-resilient crop protection plans and enhancement of global food safety nets can be developed through such integration.

2. Climate Change Impacts on Plant Health and Disease Emergence

Climate change is becoming a significant cause of the dynamics of the plant diseases. The changes in the temperatures, rainfall, carbon dioxide (CO₂) in the atmosphere and the increased occurrence of extreme weather conditions affect plant physiology and biology of pathogens. These environmental variations influence the survival, reproduction, dispersal and effectiveness of pathogen infections. Thus, climate change will alter the geographic distribution, incidence, and severity of many plant diseases (Garrett et al., 2021).

One of the most important climatic conditions that regulate disease development of plants is temperature. The majority of bacteria and fungi have their optimal temperature ranges for growth and infection. The increased temperature may hasten the growth of pathogens and reduce latent periods which allows more infection cycles during a growing season. Faster reproduction by pathogens will compound disease pressure in most crop systems (Kumar and Mukhopadhyay, 2025). Global warming has already increased the risks of diseases eruption in numerous crop systems. As an example, in most wheat-producing areas, warmer conditions have been associated with the risk of epidemics of wheat rust (Hussain et al., 2025).

Plant pathogens are also influenced by climate change in terms of geographic distribution. It has long-term global projections that have shown that most pests and pathogens of crops are moving towards higher latitudes as temperatures rise. A survey of historical notes of crop pathogens showed that many plant pathogens and pests had moved polewards at a rate of 2.7 km per year (Tagyan et al., 2025). These changes may subject disease-free agricultural lands to new pathogens, and the farmers within these lands might lack experience to handle these agents thus becoming prone to crop losses.

Humidity and precipitation have a robust effect on the epidemiology of plant diseases. Excessive humidity and extended duration of leaf wetness favor the germination of spores, pathogen infections, and disease transmission. Most of the foliar pathogens, such as rusts, mildews and blights, are infection dependent on the presence of moisture. Climate predictions suggest that most areas will have more fluctuations in the patterns of rainfall, such as excessive rainfall and floods (IPCC, 2021). These circumstances have the potential to augment disease outbreaks by promoting the pathogen spread and infection. For instance, the soil pathogens can be spread when there is heavy rainfall due to water transportation and contaminated sediments (Rashmi et al., 2022).

Climate change related to drought conditions also affect the health of plants and their vulnerability to diseases. Plant immune system can be compromised by water stress and less effective defence mechanisms can be developed. The stressed plants due to droughts are usually susceptible to opportunistic pathogens, such as *Alternaria* and *Fusarium* species. Such pathogens may infect susceptible crops and lead to significant losses in the yield (Trivedi et al., 2020). Stress due to climate thus provides conducive environments in various cropping systems for the occurrence of diseases.

New fungal pathogens present a major threat to world agriculture. Fungus attacks most of the staple crops such as wheat, rice, maize, and potatoes. These pathogens are able to propagate quickly and are able to adjust to new environmental factors. Fungal plant diseases have been estimated to annually destroy sufficient food to feed more than 600 million individuals, clearly showing the significant impact on food security around the world (Fisher et al., 2022; Fones et al., 2020). There is also a possibility that climate change will increase the threat of pathogen outbreaks by modifying the environmental conditions in favor of the survival and infection of the fungi.

There has been a significant increase in the atmospheric CO₂ concentrations during the past 100 years. Before the industrial revolution, the concentration of CO₂ was around 280ppm, but the concentration in the world today exceeds 420ppm in 2023 (Nakamura et al., 2025). High CO₂ levels may affect the physiology of plants such as changes in photosynthesis, leaf morphology and the structure of the canopy. These alterations are able to change the microclimate in crop canopies and influence the process of pathogen infection. For example, a higher level of canopy density can produce humid microbes, which support foliar pathogens (Sharma and Verma, 2019). Nevertheless, CO₂ increases the effects of plant disease and requires host pathogen interactions.

Climate change is increasing the rate of extreme weather events that can lead to the occurrence of diseases. Pathogens can be spread by flooding, storms, and strong winds to extensive geographic locations. Under ideal weather conditions, fungal spores carried by wind may travel hundreds of kilometers. This has been associated with several significant crop pathogens, such as rust fungi (Lavanya, 2025). Soilborne pathogens can also be dispersed and contaminated by flooding and increase the risk of the onset of diseases.

Besides the impact on the environment, climate change may also affect the development of plant diseases in relation to the interaction with agricultural activities. Modifications in the systems of cropping, irrigation, and control of pests can interact with climatic conditions and affect the dynamics of diseases.

The study of these interactions is critical in determining disease risks and in coming up with efficient management interventions.

3. From Plant Disease to Food Chain Contamination

Plant diseases are not only a factor that determines crop productivity but also food safety. The food chain can be exposed to biological and chemical risks through infection of crops by fungal, bacterial, or viral pathogens. Field contaminants could be retained during harvesting, storage, processing and distribution. Thus, the safety and quality of food systems strongly depend on the health of the plants (Rizzo et al., 2021).

The growth of mycotoxins by plant-pathogenic fungi is one of the most significant processes that correlate plant disease to food contamination. Mycotoxins are fungal toxins, which are secondary toxic metabolites of such genera as *Aspergillus*, *Fusarium* and *Penicillium*. These fungi attack crops prior to harvesting or storage and the toxins formed are not biodegraded and retained in food and feed products after processing. According to global evaluations, about 25% of food crops contain mycotoxins every year, and it presents a significant hazard to food safety and human health (Eskola et al., 2020).

Aflatoxins are regarded as the most dangerous of these toxins. They are primarily caused by *Aspergillus flavus* and *Aspergillus parasiticus* which attack crops like maize, peanuts and tree nuts. The International Agency for Research on Cancer classifies aflatoxin B1 as a Group 1 human carcinogen. Aflatoxins have been linked to chronic exposure causing hepatocellular carcinoma, immune impediment, and growth retardation in children (Shan, 2019). Aflatoxin contamination is one of the biggest food safety issues in most tropical and subtropical areas. Stressors found in the environment, including drought and elevated temperatures, make plants vulnerable to fungus and toxin generation (Valencia-Quintana et al., 2020).

Another important category of plant pathogens that cause food contamination is species of *Fusarium*. It is a type of fungi that infects cereal plants such as maize, wheat and barley in the season they are growing. They secrete a number of mycotoxins such as fumonisins, deoxynivalenol (DON), and zearalenone that often contaminate cereal grains. Fumonisin have been especially implicated in the infections of maize and have been associated with the disease of animals, including equine leukoencephalomalacia and porcine pulmonary edema. Exposure of fumonisins to people has been linked to esophageal cancer and neural tube defects (Eskola et al., 2020). During infection in fields, these toxins

can be retained into crops and they can keep growing under the favorable conditions of storage.

Plant diseases also may contribute to the contamination of food by making the crops subject to colonization by human-pathogenic bacteria. Fresh fruits and vegetables may be contaminated with pathogens including *Listeria monocytogenes*, *Escherichia coli* O157:H7 and *Salmonella enterica*. These microorganisms are able to live on the surfaces or inside plant tissues. Bacterial survival and growth rely on damaged or diseased plant tissues, which provide nutrients and entry points, which sustain their survival and growth (Luna-Guevara et al., 2019). Fresh produce is more susceptible since it is rarely cooked or processed in any way, which means that pathogens can get to consumers without being destroyed.

Another mechanism which connects the relationship between plant disease and food contamination is the tissue damage by the pathogens. Most of the fungal diseases destroy the plant cell wall and liberate nutrients that support the growth of the microorganisms. Such destroyed tissues provide good environments to secondary colonization by microbes. Infected crops may therefore easily harbor opportunities to breed opportunistic bacteria and other spoilage microorganisms. The process enhances microbial loads and could affect the food safety and shelf life (Rizzo et al., 2021).

The postharvest periods are also very critical in terms of transfer of plant pathogens and contaminants into the food chain. There are possibilities of crops being infected in the field, and still having fungus pathogens in subsequent storage and processing. Poor storage conditions especially high temperature and humidity can encourage fungal proliferation and toxin production. It has been estimated that approximately 14% of all food produced all over the world is lost between harvest and retail, partially because of microbial spoilage and contamination (Dongyu, 2019). Good postharvest management is thus necessary in order to minimize the development of infectious diseases and food safety risks.

Climate change also enhances the relationship between plant disease and food contamination. The environmental factors that may support fungal infection and production of mycotoxins may include high temperature, drought stress, and uneven rainfall. It is proposed that the climate change can increase the area of aflatoxin contamination in producing areas (Dövényi-Nagy et al., 2020). These changes may put new groups of individuals at risk of foodborne toxins and may escalate the costs of food safety risks.

Plant diseases constitute a critical pathway into the food chain through which biological and chemical contaminants enter the chain. Contamination of food products is due to field infections, tissue damage and postharvest microbial growth. It is necessary to comprehend these mechanisms in order to formulate integrated disease management and food safety strategies. An approach that can be used in early detection and prevention of contamination risks within the food system is a One Health approach, which combines plant health, environmental monitoring, and surveillance of human health.

4. Food Safety and Public Health Implications

Contamination of food by plant diseases is a serious world-wide public health problem. Acute diseases (i.e. food poisoning) and chronic (i.e. malignancies, developmental disorders, immune dysfunction) are also triggered by pathogens and toxins produced by diseased crops. These risks are not limited to specific demographics: infants, young children, pregnant women, the elderly, and immunocompromised individuals are prone to them due to the deficit of physiological resilience and a lack of means to process toxins or resist microorganisms (WHO, 2024).

The largest chemical risk is mycotoxins which are of plant origin. The aflatoxin B1 is chronically exposed, with hepatocellular carcinoma being strongly linked with the aflatoxin B1 *aspergillus*. Neural tube defects, immunosuppression, and growth retardation in children have been associated with fumonisins and deoxynivalenol, which is produced by the species of *Fusarium* (Gonya et al., 2024). Globally, some 4.5 billion people are estimated to suffer chronic exposures to mycotoxins, with the largest concentration taking place in southeast Asia, Sub-Saharan Africa, and parts of Latin America (Koshiol et al., 2026). These sustained exposures are observable as quantifiable negative consequences to the public health, leading to high levels of stunting and hepatic illness among the population subjected to such exposures.

Bacterial contamination of vegetable food is another very serious issue. Human pathogens *Listeria monocytogenes*, *Salmonella enterica*, and *Escherichia coli* O157:H7 and have the ability to survive on fresh produce and minimally processed crops. During 2009-2022, fresh fruits and vegetables were identified as the cause of more than 500 foodborne outbreaks in the United States and caused thousands of illnesses and several deaths (Huang et al., 2020). The most severe cases and hospitalizations were represented by the vulnerable groups, especially the younger group of children less than five years old and the older population group. In addition, immunocompromised patients i.e. HIV/AIDS, or those undergoing chemotherapy have a high probability

of getting severely ill or dying due to these bacterial contaminants (Vachon et al., 2025).

The international trade, food habits of the population, and climatic change all play a major role in exposing the world to food hazards of plant origin. The crops that are traded globally, such as maize, wheat, peanuts, and tree nuts, are vectors of pathogenic organisms and spread disasters that were never witnessed in the destination countries. These risks are exacerbated by climate change that changes environmental conditions, which allow proliferation of pathogens. Low precipitation, high temperature and drought stress favor fungal infection and increase the mycotoxin concentration. Indicatively, the risk of aflatoxin in maize has increased in southern Europe due to temperature increase and long droughts, and thus temperate populations are at risk (Focker et al., 2023). In a comparable manner, the East African and Southeast Asian areas have a greater aflatoxin contamination during hot dry seasons, which relates to the spikes in liver cancer and other chronic illnesses.

The socioeconomic and geographic factors have a disproportionate effect on vulnerable populations. Poor communities, subsistence farmers and rural communities do not have access to proper storage facilities, safe irrigation facilities and regulatory measures. The inefficiency of post-harvest management leads to the enhancement of fungal growth and mycotoxin build up. For instance, aflatoxins can reach levels above $100\mu\text{g kg}^{-1}$, more than 50 times the EFSA limit of $2\mu\text{g kg}^{-1}$ of aflatoxins in human consumption of maize stored at high moisture in poorly ventilated warehouses (Ayeni et al., 2020). Young children and pregnant women exposed to contaminated crops are the most affected by the effects of stunting, developmental disorders and birth defects.

Risk communication is a very important component of food safety strategies. Clear and accurate information is a requirement to obviate exposure especially in the vulnerable groups. Regulatory authorities, such as EFSA, FDA, and WHO, set levels of mycotoxins that should not exceed a specific point and develop monitoring systems that could identify contamination of food products. As an example, EFSA defines aflatoxin B1 in maize at $2\mu\text{g kg}^{-1}$, but the FDA recommends $20\mu\text{g kg}^{-1}$ as an action level for human food (U.S. Food and Drug Administration, 2021). Exposure can be minimized at the community level by educating individuals on safe harvesting, drying and low moisture storage. The process of dehydration of maize to a moisture content of less than 12% stops the growth of fungi and the formation of mycotoxins, and similar strategies can be used with other cereals and nuts (Gong et al., 2024).

The well-developed risk communication strategies should also be able to accommodate the literacy levels, cultural practices, and the local food

systems. Pictorial guidelines, community-based training, and mobile phone alerts have shown a 30-50% decrease in aflatoxin exposures in African field research. Such strategies are especially important for the smallholder farmers and low-income consumers who may not even be aware that there is a danger of contaminated crops. The timely and effective food safety information dissemination requires the collaboration of public health authorities with agricultural extension services and the local communities (Alabi et al., 2025).

5. Integrated Risk Assessment and Governance under One Health

The coordinated management of the risks of plant disease and food safety hazards necessitates an orderly risk assessment and policy formulation. It must be supported by evidence and cross-sectoral cooperation aimed at addressing the interests of human, animal, plant, and environmental health. One Health approach provides a functional model of harmonizing the surveillance, regulation, and response (FAO, 2022).

Comprehensive risk assessment tools are based on synthesis of data of environmental monitoring, pathogen surveillance, climate studies and food-system exposure to provide a holistic assessment of potential hazards. The tools facilitate the measurement of the probability of hazards and help in decision-making regarding the limits of the regulation, the distribution of resources and the method of early interventions. For instance, risk-ranking frameworks developed by FAO combine the quantitative data of crop contamination with the climate-risk factors to help the nations set priorities in their food-safety and to optimize the process of resource allocation (FAO, 2024).

Regulations provide legal limits of the unsafe hazards in food. The Codex Alimentarius Commission develops standards of chemical and microbial contaminants which are internationally accepted, such as mycotoxins, heavy metals, and zoonotic pathogens. A harmonized international trade regime and the need to protect the health of the population make codex risk analysis structured around hazard identification, exposure assessment, and risk characterization (Cioca et al., 2023). These frameworks are modified to national food safety systems to reflect the local epidemiological information, dietary patterns and climatic susceptibility.

Effective cross-sector coordination promotes the operational capacity to deal with the risk of plant health and food-safety. Protection and prevention organizations of plants, public-health laboratories, agricultural and weather services are integrated in surveillance systems. Common databases with

pathogen detection, toxin presence in food, and environmental warning information enhance the ability to detect them early and respond to the incident with coordination. In Southeast Asia, food-safety networks in the region facilitate reporting of contamination of mycotoxins in staple grains, hence rapid policy response and advisories to the population (Lim et al., 2018).

There are specific instruments of policy (e.g. early-warning systems, decision-support tools, financial incentives) that make people more prepared and comply with the instructions. Predictive systems that use remote sensing and real-time weather information can alert when conditions are favorable to fungal outbreaks or toxin concentration before crop harvesting. The policy makers can make warnings or use focused interventions to minimize contamination. Multisectoral data synthesized with the assistance of the decision-support tools to prioritize the interventions based on the vulnerability of the population and the severity of risks (Inglis et al. 2024).

Risk communication is also important in effective governance, at all levels with the stakeholders. The targeted communication strategies make sure that farmers, processors, traders, and consumers are aware of hazards, prevention strategies, and regulatory standards. In one such instance, the localization specific food-safety advice has been provided through digital platforms that are used within community extension programs based on seasonal risk forecasts. Such platforms have established better adoption of the best practices in postharvest in smallholder systems (Manzoor et al., 2025).

The capacity to assess risks, and to govern is enhanced by international collaboration between regulatory agencies, inter government agencies and civil societies. The One Health Joint Plan of Action (2022-2026) is a report prepared by FAO, WHO, UNEP, and WOAHA that offers a roadmap regarding integrated responses to health menaces on the interface of the human, animal, and environmental systems. It emphasizes cross-sectoral surveillance, laboratory capacity, and data sharing as well as harmonization of policy to deal with food safety and the emergence of pathogen threats across the globe (Milazzo et al., 2025).

Plant biosecurity should also be part of food safety in the governance mechanisms. The threat of new pathogens, which at the same time may enter into food systems, is reduced by the Biosecurity policies of the importation of plants, border controls, and pest-free certification. The collaboration of agricultural authorities and trade regulators helps to balance between biosecurity and economic goals (Alawneh et al., 2025).

6. Climate Adaptation Strategies for Resilient Food Systems

The anthropogenic climate change alters temperature, rainfall distribution, and frequency of extreme weather conditions, which increases the prevalence of plant diseases, proliferation of pests, and accumulation of mycotoxins. Those changes are a threat to crop productivity, food quality and human health. Climate adaptation goals are to improve food systems resilience using genetic, agronomic, technological, and policy interventions to provide a sustainable plant health and food safety under changing climatic conditions (Loboguerrero et al., 2019).

Climate agronomic practices alleviate pressure of environmental stress and disease. Conservation tillage enhances the soil structure, water retention, and biodiversity of microbes, which suppress pathogens on the soil (Lal et al., 2021). Crop rotation, intercropping and cover cropping break the cycle of life of pathogens hence reducing the inoculum pressure. For example, the swamping of cereals with non-host legumes may lower the number of soil-borne fungi (Zong et al., 2024). Optimal soil organic carbon helps in stabilizing plants and improving cycling of nutrients which promotes stability in yield and resistance to pathogens.

It is necessary to develop and implement climate-resilient cultivars. The physiological performance during abiotic stress is maintained by breeding heat, drought and disease tolerance. Genetic selection, marker-assisted breeding and gene editing methods have expedited the production of resistant cultivars. Heat resistant line of wheat show improvements in yield by 20% and maize drought resistant hybrids demonstrate 10-15% yield gains under extreme heat and water scarcity conditions respectively (Zhao et al., 2018). Such cultivars also increase predictability of food supply during uncertainty in climatic conditions.

Integrated Pest and Disease Management (IPDM) offers dynamic management of the climate-induced pests and pathogens. IPDM will be an integration of resistant plants, biological control agents, sensible use of chemicals, cultural control, and foresees monitoring. An integrated system of decision support which includes the pest life cycles as well as the weather forecasts are used to optimize the timing of intervention and minimize use of redundant pesticides. Predictive-based fungicide application can minimize chemical usage by 43-50% without reducing the control of disease suppression (Lázaro, et al., 2021). Antagonistic fungi and beneficial rhizobacteria are examples of biological control agents that improve immune response in plants

as well as alleviating the use of synthetic chemicals, leading to the sustainability of the ecosystem (Ons et al., 2020).

The use of water management innovations is critical in reducing drought and the spread of pathogens. The drip irrigation, deficit irrigation and rainwater harvesting enhance the regulation of soil moisture and minimize the growth of pathogens. The deficit irrigation can be under control to minimize the length of the wetness of leaves, which will decrease the frequency of fungal infections. Drip irrigation has been found to be 30-50% more efficient in water use than conventional flood irrigation (Ashour et al., 2020). Such interventions stabilize crop health, decrease variability of yield as well as pathogen-related food contamination.

The strategies used in the post-harvest to enhance food quality and safety are crucial. Controlled-atmosphere silos, hermetic storage, rapid drying and temperature-controlled storage help to prevent the growth of fungi as well as mycotoxins. It is important to maintain the grain moisture level less than 12% percent in order to prevent the growth of fungi. The use of hermetic storage bags has decreased postharvest losses exposed to high-humidity and temperature in the smallholder systems. These interventions are especially applicable because of climate change which makes storage more vulnerable (Ngoma et al., 2024; Dijkink et al., 2022).

Digital technologies and early-warning systems that improve the anticipatory ability of farmers and policymakers. Vegetation indices, soil moisture sensors, and climate-forecasting models have been predicted using satellites that forecast crop stress and favorable conditions of pathogens. Digital advisory applications and mobile applications are used to disseminate real-time planting, irrigation, disease management guidance, thus enhancing mitigation strategies adoption and vulnerability reduction (Herrero et al., 2020).

Adaptation is based on policy instruments and institutional structures. National adaptation plans encourage climate-wise farming, ease access to climatic services, enable economic encouragements, and enhance expansion programs (UNFCCC, 2025). Insurance schemes such as weather-index insurance protects farmers against weather variation, which makes farmers to adopt resilient practices. When the policy is designed by incorporating climate, pest, and food safety information, the resources will be prioritized to the high-risk crops and areas.

The One Health paradigm leads to cross-sectoral coordination, which makes a system resilient. The combination of plant health surveillance, environmental surveillance, and food safety evaluation allows the proactive control of the

emerging risks. Regional partnerships also help in harmonized early warnings, quick reaction to intercontinental pests, and knowledge management in order to reduce systemic weaknesses. One Health approaches allow optimization of the effect of adaptation by aligning agricultural, environmental, and public health sectors and reducing the number of unintended impacts of change in the ecosystems and communities (Hoffmann et al., 2022).

A combination of these strategies would make the food systems more resilient, protect the health of plants, sustain crop productivity, and guarantee nutritious and safe food. Climate-sensitive strategies, resilient varieties, adaptable management and policies can help food systems to cope with climate change and extremes. These combined strategies can be crucial to ensure the agricultural productivity, food safety and ecosystem and human health under the dynamic climate.

7. Conclusion

The increase in climate change is altering the interactions between plants and pathogens and is increasing the susceptibility of world food systems. High temperature, unusual rainfall, and the growing number of extreme weather patterns reorganize the distribution of disease and promote the geographical spread of plant pathogens. As a result, losses in crop yields are increased and the chances of food contamination through mycotoxins and microbial hazards are increased. Therefore, plant health is critical concern between the sustainability of agriculture and food safety since diseased crops may act as a source of biological and chemical contamination threatening human and animal health. Conserving plant health is thus not only necessary in order to maintain crop productivity, but also ensure the integrity of the food chain as a whole. To meet these related issues, a unified One Health approach is crucial; coordinated monitoring, climate-prone risk evaluation, and inter-sector cooperation can support the initial identification and control of emerging threats. At the same time, other interventions that can enhance agricultural resilience include the production of climate-resistant crop varieties, adoption of sustainable agricultural management, enhancement of post-harvest mechanisms, and the use of digital early-warning systems. Adequate scientific cooperation, good governance and active adaptation policies are important to the attainment of safe and sustainable food systems under climate change. Anthropocentric policies that endorse plant health as a priority area in climate and food-safety regulations will play critical roles in protecting world food security and human health in the next few decades.

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CHAPTER 2

Climate Change, Mycotoxins, and Food Safety: Emerging Risks in Crop-Based Food Systems

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Abstract

Climate change is altering food crop-based systems and increasing the risks to food safety. Higher temperatures, changed rainfall distribution and increased concentrations of CO₂ gases in the atmosphere alter the ecology of fungal plant pathogens. These changes facilitate growth of fungi, increase geographical dispersion and pressure of diseases on major crops. Consequently, the amount of mycotoxins in cereals, nuts, and oilseeds is rising and has become more unpredictable. New contamination challenges are now being experienced in former low-risk production regions. Climate change also alters the toxin

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profiles and permits the co-occurrence of various mycotoxins in a particular commodity. Such trends confront the current monitoring, risk-assessment and regulatory systems which are based on past data. The growing variability reduces the accuracy of traditional forecasting and sampling which increases the uncertainty in the exposure assessment. Increased exposure to mycotoxins is a major health hazard, particularly in chronic dietary consumption and indirectly through animal products. Vulnerable populations, including infants and communities dependent on staple crops, might be at greater risk due to climate change. There are also economic effects due to rejected exports and stricter standards of trade. The chapter provides a review of evidence that climate change results in fungal pathogen dynamics and mycotoxin contamination. It evaluates the consequences of food safety, human health, and international trade. The chapter highlights the need to use climate-based monitoring, early warning systems, and flexible risk management to protect future food systems due to climate change.

Keywords: Mycotoxins, Food safety, Climate change, Aflatoxins, Predictive modeling

1. Introduction

Climate change is a global phenomenon that is increasingly affecting food system's safety and stability. There is a changing climatic condition because of rising temperatures, altered precipitation pattern and increased levels of carbon dioxide in the environment, which are changing the conditions of crop production. Such transformations have a direct impact on the growth, distribution and competitiveness of fungal plant pathogens, most of which are capable of synthesizing toxic secondary metabolites. Recent food safety analyses indicate that climate change is one of the key factors in the emergent biological risks in agricultural production (Misiou and Koutsoumanis, 2022).

Crop food systems are particularly susceptible to fungal hazards caused by climate. Plant pathogens are sensitive to changes in temperature and moisture due to their short life cycle and high adaptive ability. The patterns of warming allow the rapid colonization, higher rates of sporulation, and prolonged activity of the pathogen. Simultaneously, the alterations in rainfall patterns alter the humidity in the canopy and duration of wetness on leaves, which are the determinants of infection spread. These changes in the environment increase the overall disease pressure of most agro-ecosystems (Perrone et al., 2020).

Mycotoxins represent one of the major food safety issues associated with the adaptation of fungi in changing climatic conditions. These chemicals contaminate foods like maize, wheat, barley, nuts and oil seeds. Humans

are exposed through direct ingestion of the contaminated plant products or indirectly by the animal derived products. Climate change affects growth and toxin production of fungi, resulting in variation in the occurrence and level of contamination (Moretti et al., 2019; Kos et al., 2023).

In recent literature, it has been highlighted that climate change not only changes the magnitude but also the structure of food safety risks. Shifts in environmental conditions change the historical patterns of contamination and undermine the credibility of the traditional monitoring methods. Consequently, the spread of mycotoxin contamination exhibits complex spatial and temporal dynamics and the presence of several toxins in the same commodity (Casu et al., 2024).

Mycotoxins are considered one of the most critical food contaminants in the world, from regulatory and other health perspectives. Long-term dietary exposure is linked to negative health effects therefore prevention is important. The issue of climate change is now recognized as a contributor to a higher level of exposure uncertainty and the incapability of current risk assessment frameworks to rely on historical data (Liu and Van der Fels-Klerx, 2021).

The management of food safety is greatly important in understanding climate-based variations in the dynamics of fungal pathogens and mycotoxin risks. A combination of climate science, plant pathology and food toxicology offers a basis for adaptive risk assessment and mitigation. The chapter summarizes the new evidence on climate change related to alteration in fungal threats in crop-based food systems and evaluates potential consequences of these changes in food safety strategies in the future.

2. Climate Change Drivers and Shifts in Fungal Plant Pathogen Dynamics

Climate change is altering the abiotic environment that determines the ecology of fungal plant pathogens in food system crops. The average temperature of the surface has increased by approximately 1.1-1.2 °C above pre-industrial temperatures (Masson-Delmotte et al., 2021). The fungal metabolism, growth, and efficacy of infection are directly regulated by temperature. Many plant-pathogenic fungi have a range of 25 to 35 °C, which has become more frequent at critical crop growth stages (Kumar and Mukhopadhyay, 2025). An increase in temperatures reduces latent periods and enhances sporulation, increasing the number of disease cycles throughout a season and increasing the risk of epidemics (Raza and Bebbber, 2022).

Fungal pathogens are influenced by heat, which affects their distribution and survival. Increasing temperatures are removing climatic barriers to fungal survival and overwintering and permit pathogens to move to higher latitudes and elevations (Velásquez et al., 2018). The changes introduce new production regions to new disease complexes, and the local varieties of crops are frequently not sufficiently resistant. Consequently, the disease pressure increases even without a change of agronomic practices (Bastas, 2022).

Fungal infection only spreads when there are humidity and moisture. The condition of high relative humidity and prolonged wetness of the leaf is vital in the germination of its spores and host penetration (Romero et al., 2022). Climate change increases the frequency of heavy rainfall and extends the wetness of canopies by increasing the intensity of the hydrological cycle. The presence of short periods of high humidity, particularly due to the combination with high temperatures, may cause sudden outbreaks of diseases (Misra et al., 2020).

The pathogen dynamics are also influenced by drought. Water stress compromises host defense and alters microclimate in the canopy. Some fungi can withstand low water activity and can survive in dry conditions. Droughts and rains selectively breed these stress-adapted species and alter the fungal population to more aggressive and competitive pathogens. An increase in the variability of rainfall is associated with an increase in the year-to-year severity of the disease (Milici et al., 2020).

Host-pathogen interactions are also altered by the increase of CO₂ in the atmosphere. The present CO₂ concentration is over 420 ppm and will increase within the century. Increased CO₂ stimulates plant carbon uptake and modulates tissue structure, including carbon-nitrogen ratios and defensive metabolites. Experimental studies demonstrate more fungal colonization at high CO₂ levels, particularly with warming and adequate moisture (Smith and Luna, 2023; Perrone et al., 2020).

The effects of temperature, humidity and CO₂ are synergistic and not independent. Their interaction leads to fungal growth, virulent changes as well as competition. The variability of climate favors the emergence of thermotolerance and phenotypic plasticity in populations of pathogens, which increases the frequency and unpredictability of outbreaks. This is expected to intensify the pressure of fungal diseases in future crop systems and an increasingly problematic issue in crop productivity and food safety (Kos et al., 2023; Gullino et al., 2018).

3. Climate-Driven Changes in Mycotoxin Contamination of Major Crops

The changing climatic conditions are shifting the distribution patterns of mycotoxins in the major food and feed crops around the world. Fungal growth and the production of secondary metabolites are highly controlled by temperature, moisture, and atmospheric CO₂. These factors determine the prevalence of mycotoxins in future climatic conditions. Predictive models indicate that warming and climate variability would increase the risk of mycotoxin in most staple crops. The risks vary in terms of products and groups of toxins (Kos et al., 2023; Medina, 2023).

Maize, wheat, and barley are sensitive to climate-driven changes in mycotoxin. Under the warming conditions, maize exhibits the greatest projections of aflatoxin B₁ contamination. An increase in climatic temperature of +2 °C is significant in increasing the climate suitability of *Aspergillus flavus* in the temperate areas. Model-based projections indicate that aflatoxin contamination levels will exceed the current regulatory limits in southern and central Europe by the middle of the century. These shifts are associated with the rise in temperature in summers and higher drought stress during kernel filling (Alvito and Assunção, 2022; Leggieri et al., 2021).

In the case of wheat and barley, there are toxin-specific reactions. More humid and warmer conditions favor the *Fusarium* species and trichothecenes production like deoxynivalenol (DON). Climate predictions indicate that there is a high risk of DON in northern and western Europe because it is likely to experience higher rainfall at anthesis (Casu et al., 2024). On the contrary, the southern areas can have a lower DON but higher aflatoxin pressure. This Geographic variation reflects the differences in the region concerning the interaction of temperatures and moisture (Liu and Van der Fels-Klerx, 2021).

Climate-induced changes in mycotoxins also affect oilseeds and nuts. High temperatures and extended drought promote aflatoxin development in ground nuts and tree nuts. Experiments in the field demonstrate that the concentration of aflatoxins may increase several times in the presence of heat and water pressure. These are assumed to be high in semi-arid and Mediterranean climatic conditions. Consequently, there are increasing food safety risks and trade risks on the export of nuts (Kluczkowski et al., 2025; Owolabi et al., 2023).

The relative significance of individual mycotoxins is also influenced by climate change. The thermotolerant fungi are becoming more competitive than the species adapted to lower temperatures. This is changing the preference towards aflatoxins to less competitive toxins like ochratoxin A or zearalenone

in certain areas. Higher CO₂ also alters toxin profiles by changing fungal expression and nutrient content of the host. Experimental research shows increased toxin production in each biomass unit at high CO₂ combined with warming (Hay et al., 2021; Cervini et al., 2021).

Overall, climate change is linked with the increase in mycotoxin load in major crops. The tendency of risks is becoming more product- and toxin-specific. Maize and nuts are increasing in risk of aflatoxins as the small grains face regionally variable *Fusarium* pressure. Such trends undermine the current monitoring and control structures. Climate-aware risk assessment will be required to ensure food safety in food-based systems (Chhaya et al., 2022).

4. Implications for Food Safety and Human Health

Mycotoxin contamination is a direct risk to food safety and human health caused by climate factors. Mycotoxins primarily enter our diet via cereals, nuts, oilseeds and processed foods derived from these products. The most common sources of global dietary exposure are maize, wheat, rice, and peanuts, as they are widely consumed and easily infested by fungi (Mafe and Büsselberg, 2024). Climate change is increasing the frequency of contamination, as well as the concentration of toxins, exposing people to chronic low-dose toxins. This impact is significant in those areas that rely on staple crops and have less dietary diversity (WHO, 2023).

The main route of exposure is through dietary intake, but the indirect pathways are also involved in the cumulative burden. Mycotoxins or their metabolites may transfer into animal products when animal food is contaminated (WHO, 2023). For example, aflatoxin B₁ is metabolized to aflatoxin M₁, which is released in milk and remains stable throughout the process. Monitoring indicates that aflatoxin M₁ is commonly found in dairy products, particularly in hot dry seasons. In this way, increases in feed contamination due to climate change increase human exposure through milk and dairy (Jahromi et al., 2025).

Mycotoxins may lead to severe health issues in the long-term. Aflatoxins are categorized by the International Agency for Research on Cancer as a Group 1 human carcinogen, which is closely associated with hepatocellular carcinoma (Awuchi et al., 2022). Research indicates that long-term exposure to aflatoxins with hepatitis B infection increases the risk of liver cancer by more than ten times. The deoxynivalenol affects immune and gastrointestinal system, whereas fumonisins have been linked to esophageal cancer and neural defects. These hazards are enhanced under the changing climate conditions, and more than one mycotoxin may exist in the same food (Adaku Chilaka and Mally, 2020).

Climate change also alters exposure patterns through the variability of introducing time. Severe weather may cause an impulsive increase in contamination, which reduces the post-harvest mitigation responses (Ali et al., 2020). This lowers the effectiveness of sorting, blending, and processing methods. This is particularly dangerous to infants and young children since they consume more food in comparison with their body weight and lack detoxification capacity. Poor surveillance and weak enforcement of regulations contribute to inequality in exposure in countries with low- and middle-income (Gonya et al., 2020).

Regulatory systems are very important in mitigating the risks associated with mycotoxins. The World Health Organization (WHO) and the Food and Agriculture Organization (FAO), in the Codex Alimentarius Commission, established international limits on mycotoxins in food and feed. These limits are supposed to protect the health of the people and facilitate international trade. Toxicological and exposure testing by joint FAO/WHO Expert Committee on Food Additives (JECFA) sets these standards. The recent meetings of Codex explicitly admit that climate change may exceed the limits and the uncertainty of exposure in the future (FAO, 2026).

The FAO has advanced an integrated system of risk management of mycotoxins. The system incorporates the use of climate-sensitive agricultural methods, enhanced post-harvest storage, and biologically controlled methods. WHO emphasizes the integration of food safety management through risks and the utilization of the revised dietary exposure evaluations, which consider climatic variability. The two organizations share the focus on adaptive surveillance systems and climate-informed regulation. It is becoming widely recognized that climate projections should be included in exposure assessment and setting of standards to protect the health of the people in future climate conditions (Rhouma, 2025).

5. Monitoring, Prediction, and Early Warning Systems

The control of climate-induced mycotoxin risk is based on effective monitoring and forecasting. Post-harvest testing is no longer sufficient as the level of climate variability increases. The models are now predicting contamination before the harvest by taking into consideration temperature, rainfall, humidity and the growth stages of the crop. It is more accurate when the models analyze the significant periods of infection like flowering and grain filling (Wang et al., 2022; Krska et al., 2022).

Process-based as well as empirical models apply to major crops. In the case of maize, the models predict the risk of aflatoxin B₁ using heat and drought indices. Several years of modelling have shown that there is a close correlation between temperature extremes and the contamination rates. The models of deoxynivalenol are based on rainfall and humidity at anthesis in wheat and oats. These tools can be used to make region-specific risk maps on current and future climates (Gbashi et al., 2024; Wang et al., 2024).

Field sampling is now combined with spatial data within surveillance systems. Weather networks are connected to contamination databases by national and regional programs which provide a better early detection of new hotspots. Nevertheless, spatial coverage is uneven particularly in regions of low resources. Climate change requires harmonized and continuously monitored production zones (Casu et al., 2024; Mu et al., 2024).

Remote sensing provides risk information on mycotoxins with high-resolution environmental information. Measures derived using satellites such as temperatures of the surface of the land, moisture of the soil, and vegetation indices, point to stress conditions that promote fungal infection. According to recent research, combining microwave and optical remote sensing with climate information helps to boost the early warning capabilities. Geospatial models of aflatoxin contamination, which are based on satellites, can identify high-risk regions in maize several weeks before harvesting (Castano-Duque et al., 2023; Fischer, 2025).

Machine learning and AI increase the accuracy of prediction. They are very useful in capturing non-linear constant interactions between climate variables, crop traits and management practices. Machine learning approaches are more effective than conventional statistics in multi-mycotoxin forecasting. Explainable AI devices show important contaminating drivers to make them more transparent and reliable. The systems support the decision-making process of farmers, regulators and processors (Aggarwal et al., 2024).

Monitoring and early warning systems of climate change are important for proactive food safety. Climate models, surveillance networks, remote sensing, and AI can be combined to provide risk mitigation in time. These tools will become even more important as climate change increases the strain of mycotoxins on crop-based foods (Mu et al., 2024).

6. Adaptation and Risk Management Strategies across Food Systems

The growing risk of mycotoxins due to climate change needs both systemic adaptation to the whole food system as well as risk-management approaches. The individual interventions can no longer be effective as the climate variability increases. The combination of field level, post-harvest management, storage and policy-based control should be effective. The goals of climate adaptation strategies are to minimize fungal infection and reduce the accumulation of toxins under future conditions (Rhouma, 2025).

The first barriers are crop and agronomic management that are at the field level. The ability to reduce fungal colonization during stress is achieved by selecting resistant or tolerant cultivars. Planting early and varying the timing of harvesting are other methods to prevent from time of peak heat and moisture. Crop rotation causes a decrease in inoculum of soil and disturbs the life cycle of pathogens. Aflatoxin accumulation in maize and nuts is closely associated with drought stress which is prevented by proper irrigation. In field experiments, it is proven that aflatoxin contamination can be reduced by more than 50% in hot conditions by eliminating drought stresses (Kos et al., 2023).

Adaptation strategies also include biological and chemical measures of control. *Aspergillus flavus* produces aflatoxins which are suppressed by competitive, non-toxic strains of the fungi. Large-scale field application reports 70-90% aflatoxin reduction in maize and ground nuts. Fungicides can limit the *Fusarium* infection if applied at the right time, but their effectiveness decreases in extreme weather conditions. As a result, the use of integrated pest-management is favored under conditions of climate change (Ortega-Beltran and Bandyopadhyay, 2023).

The management of post-harvest and storage is still considered a crucial risk management area. Severe drying of moisture content less than 13-14% inhibits fungal growth to a large extent. The storage technologies that contain less oxygen lower the growth of fungi that produce mycotoxins. It has been demonstrated that post-harvest toxin increase can be avoided even in cases of pre-harvest infection through the use of better storage methods. Climate change increases the significance of such measures due to the increase in ambient temperature and humidity during storage (Soni et al., 2020).

Processing and sorting strategies also reduce dietary exposure. Physical sorting eliminates visibly damaged grains which are the most highly concentrated toxins. Milling and dehulling reduce the concentration of mycotoxins in final products but toxins are not removed fully. This is more important in the

case of staple foods that are consumed daily. However, the effect of climate-induced increases in the baseline contamination can compromise the mitigation measures (Ijabadeniyi et al., 2021).

Regulatory and policy interventions offer a reduction of risks on a system-wide basis. Climate change derails the existing maximum limits and sampling plans, which had been founded on historical patterns of contamination. Climate-based risk forecasting in adaptive regulations is more emphasized. Compliance and risk awareness can be strengthened through enhancing surveillance, early warning systems, and training of farmers. This coordination at the international level is needed to avoid trade disruptions due to climatic causes associated with mycotoxin surges (Casu et al., 2024; Medina, 2023).

7. Conclusion

Food safety is not only a future concern but a current problem of climate change. The increased heat, moisture stress, and CO₂ have already changed the behavior of fungi and amplified mycotoxin levels in most crops. The changing conditions result in increased and unpredictable occasions of contamination and alter the regular dynamics of fungal ecology and fungal toxins.

The key concern is the increasing difference between changing climate risks and the static food safety systems that rely on them. The existing measures of controls, sampling strategies, and regulatory levels were developed under the condition of stability. When climatic variability increases dramatically, their performance declines, and uncertainty increases. It risks the safety of vulnerable people and undermines the uniformity of food quality.

To mitigate the long-term risk, it is important to incorporate climate science into food safety decision-making. Early warning systems, predictive tools and adaptive management practices should be made an integral aspect of risk assessment. There is a need to have strong coordination between agriculture, food safety, and the public health agencies. The reduction of the threats of mycotoxins under climate change is thus a strategic effort in enhancing resilient and sustainable food systems.

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CHAPTER 3

Comparison of Loaded and Unloaded Noise Test Methods Within the Scope of Annexe XIII of EU/1322/2014

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İbrahim ERGUL³

ABSTRACT

In this study, test methods for measuring noise levels in the driver's ear in Annexe XIII of EU/1322/2014, one of the delegated regulations of the type-approval regulation EU/167/2013, which determines the production and market-supply conditions of agricultural tractors, were compared. Tractor noise levels, an area where manufacturers continuously strive to improve user health and comfort, are measured using two different methods under the regulation: Test Method 1 and Test Method 2. The researchers measured noise levels in the driver's ear for five different tractors using two methods, then compared the resulting values and test procedures. The tractors have similar dimensional measurements and the same protective structure, but

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they have three different engines. In this study, the researchers compared the two methods specified in the regulation and evaluated the results for tractors equipped with different engines. They examined how engine type influences noise levels in the driver's ear under various operating conditions and identified the most suitable engine. In addition, the researchers observed how the noise level of tractors changes when the machines operate under load. The results of the study revealed that Method 1 requires more equipment than Method 2, has a longer, more complex testing process, and involves greater difficulty in applying load to the tractor. The testing team evaluated the results and ranked the tractors under load according to Method 1 as Tractor E > Tractor B = Tractor D > Tractor A > Tractor C. They also ranked the tractors without load according to Method 2 as Tractor A = Tractor C > Tractor E > Tractor B > Tractor D. Considering that farmers typically use tractors under load during fieldwork, these results indicate that selecting a tractor using Engine Type 1 would result in lower noise exposure.

Keywords: Noise test; driver's exposure to noise level; Tractor noise; Agricultural tractor; Noise test method.

INTRODUCTION

The mechanisation of agricultural machinery has exposed farmers working in this field to increased noise levels. In particular, the noise emitted by tractors with internal combustion engines can cause problems such as decreased concentration, fatigue, difficulty in communication between workers, and hearing loss for users and people around the tractor (Matthew, 1968; Lalremruata et al., 2019).

Among agricultural machinery, the most prolonged exposure to noise-related discomfort occurs in tractors, followed by combine harvesters, soil cultivation machines, and balers. For this reason, tractor manufacturers have conducted numerous studies to identify and reduce noise and vibration sources (Celen and Arin, 2003; Dewangan et al., 2005; Jahanbakhshi et al., 2017 and 20220).

The Organisation for Economic Co-operation and Development (OECD) created test codes for agricultural tractors in 1965. Member states of the organization began testing tractors for performance and reliability using the same methods, based on a joint decision. In 1970, 'environmental noise' and 'requirements for measuring noise at the driver's ear level' were added to the OECD codes (Stayner, 1988; Lierle and Reger, 1958; Egela and Hamed, 2017; Monazzam et al., 2012).

The noise level to which drivers are exposed, measured using code 5 in the OECD codes, was specified in 1977 by the European Economic Community (EEC) in Directive 77/311/EEC, which set out the conditions for the noise level to which drivers are exposed in tractors with type approval valid in member states. The directive, which requires measurement using one of two different methods with limits of 90 dBA and 86 dBA, was updated in 2009 as 2009/76/EC and again in 2014 as Annexe XIII of 1322/2014/EU (European Union, (2014)).

Many studies have been conducted to meet regulatory requirements and improve comfort inside tractor cabins. Koizumi and colleagues developed an active noise control (ANC) system that reduces low-frequency engine noise, thereby lowering noise levels around the driver's ears to acceptable levels (Koizumi et al., 2003).

Abd-El-Tawwab et al. (2000) measured noise levels inside the cab under changing road and tractor operating conditions. They found that rubber material placed under the tractor floor helped reduce noise levels around the driver's ears.

Güner (2017) compared noise and vibration levels reaching the driver in two tractors with the same characteristics but different protective structures and found that the noise level at the driver's ears was lower in the tractor with a safety-framed protective structure than in the tractor with a single-post roll bar.

Lee and Kim (2003) demonstrated through their tests that acoustic holography detects noise sources in tractors more effectively and that installing noise absorbers under the tractor cab floor reduces noise levels to acceptable limits.

Celen and Arin (2003) identified the tractor's noise sources and measured noise levels around the operator and in the tractor's external environment under different operating conditions and at variable speeds in different gear positions. They identified the lowest and highest noise levels.

De Souza et al (2023) investigated the health effects of noise exposure on individuals directly operating tractors and those in the vicinity. Tests conducted with two tractors of varying engine power found that insulation materials reduced noise and that individuals working within 7 meters of the tractors must use ear protection.

Belek and Güney (2006) identified the noise sources and reflection points that amplify noise in the tractor model they selected, which had a noise level of 87 dBA, and reduced the noise level to below 80 dBA. In their studies, they noted that flat sheet materials transmit noise through vibration, so they replaced the sheet material with composite material. It has been determined

that changing the aerodynamic shape of the engine cooling fan, changing the number of blades from 6 to 11, and using insulation material in locations close to the primary noise sources and the front firewall are methods that reduce noise levels (Belek and Güney, 2006).

The study aims to compare both test methods in terms of results, applicability, ease of use, and preference. Additionally, to investigate why method one specified in the regulation, which has not been studied much in the articles, is not preferred by manufacturers, and to determine the most appropriate method for manufacturers by examining the rationale for defining two different approaches and limit values.

MATERIALS AND METHODS

The noise level to which the driver is exposed was measured using test methods 1 and 2 specified in the regulation on five different tractors. The prototype tractors belonging to Erkunt Traktör Sanayii A.Ş. are subject to type approval tests under the EU/167/2013 Regulation on the Approval and Market Surveillance of Agricultural and Forestry Machinery. One of the conditions tractors must meet is the driver's exposure to noise levels, as specified in Annexe XIII of EU/1322/2014. The researchers compared the two different test methods specified in the regulation.

The researchers fitted the selected tractors with front roll-bar-type protective structures. Three of the tractors have 16 forward and eight reverse gears, while two have 16 forward and 16 reverse gears. Three different types of engines from two different manufacturers are used. All engines comply with Stage V emission standards, and both tractors include a Diesel Oxidation Catalyst (DOC), a Diesel Particulate Filter (DPF), and Exhaust Gas Recirculation (EGR). In this study, the researchers used two engines: one from Erkunt Traktör Sanayii A.Ş. and another from an external company. Tractors A and Tractor C have engines manufactured by the same engine manufacturer. The engine used in Tractor A has over 56 kW, so it has an SCR system. Tractors B, D, and E have engines manufactured by the same manufacturer. Tractor E has a 3-cylinder engine. The engine used in Tractor B has over 56 kW, so it has an SCR system. The tractors have the exact physical dimensions. Tractor specifications are listed in Table 1.

Table 1. Tested Tractors

Tractor Name	Transmission	Engine	Rated Engine Power
Tractor A	16+16	Engine Type 1	63 kW
Tractor B	16+16	Engine Type 2	68,5 kW
Tractor C	16+8	Engine Type 1	55,4 kW
Tractor D	16+8	Engine Type 2	52,2 kW
Tractor E	16+8	Engine Type 3	49,9 kW

A sound level meter (microphone) is used to measure noise, and the device is periodically checked for calibration by accredited calibration laboratories. The device provides measurement results in dB(A).

Methods. EU/1322/2014 Annexe XIII specifies two different test methods for the conditions applied to the driver's exposure to noise. Tractor manufacturers can test their tractors using either of these two methods. The conditions specified in the regulation are found in the sections describing test methods 1 and 2, as well as the measurement conditions. If the noise level is below the value specified below, the tractor is considered to meet the regulation's requirements.

In Test Method 1, the maximum noise level should be 90 dB(A). In Test Method 2, the maximum noise level should be 86 dB(A).

Test Conditions. There should be no extra weight on the tractor, and optional equipment and parts should not be attached. However, engine coolant, engine and transmission oils, a full fuel tank and the driver should be present on the tractor during the test. The driver's clothing should be of normal thickness, and they should not wear a scarf or hat. There should be no objects on the tractor that could affect the noise level.

Tyres should be inflated to the pressure recommended by the tractor manufacturer. The engine and power transmission components should be at normal operating temperature, and the radiator air intake ducts should be open during measurements.

On the tractor being tested, the power take-off shaft, heater fan, windscreen wipers, and other equipment that operates with the engine or its own power system may not be operated during measurements if it is thought that they will affect the noise level. However, parts that are active by design while the engine is running, such as the engine cooling fan, must be active during the test.

The test location should be open and as quiet as possible; for example, it could be an open area with a radius of 50 meters, a center section with a

radius of at least 20 meters, and a sufficiently smooth (pothole-free) and flat surface. The ground should be dry and clean if possible.

The road surface should not cause excessive tyre noise. The weather should be clear, with little or no wind. The noise level at the driver's ear caused by noise sources other than the tractor or by wind should be at least 10 dB(A) below the noise level emitted by the tractor. The test team should take all tractor measurements during testing on the same road.

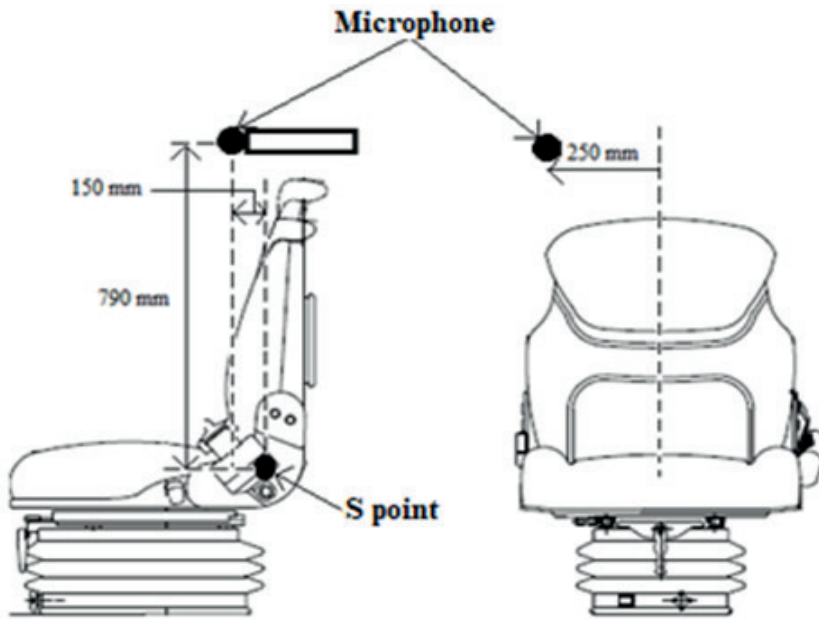


Figure 1. Microphone position (European Union, 2014).

When taking measurements, the noise measurement device (microphone) should be held 250 mm to the right or left of the seat center, as shown in Figure 1. The results from the side with higher noise will determine the test result. The (S) point defined in the regulation is the seat reference point. The microphone should be positioned 790 mm above and 150 mm in front of this point. This positioning approximately represents the driver's ear level.

Test Method 1. If the tractor being tested has a protective cab structure, the researchers conduct the initial series of measurements with all doors and windows closed. Test personnel open the doors and windows during the second series of tests if doing so does not compromise road safety; if they cannot open the doors and windows, they keep the front windows closed.

The testing team conducts the test in three stages. In the first stage, they shift the tractor into the gear that provides the speed closest to the design speed of 7.5 km/h. They start the test with the throttle fully open and gradually apply a load to the tractor, which initially runs unloaded. They measure the noise level at each load increase and repeat the measurement until the value stabilizes. The researchers continue increasing the load until they measure the maximum noise level. In the second stage, they select a different gear position than in the first stage. As in the first stage, they gradually increase the load, ensuring that the noise level measured in this stage is at least 1 dB(A) higher than the value recorded in the first stage. They repeat the test as many times as necessary to determine the appropriate gear position. The researchers take three recordings in both the first and second stages.

In the third and final stage, the noise measurement is performed without applying any load to the tractor. The noise level of the tractor moving forward in the gear position where it reaches maximum speed is measured. The test team took two recordings in this stage.

The loading method specified in the first and second stages was performed by pulling another tractor with a 10-metre-long rope attached to the tow bar of the tested tractor, as shown in Figure 2. Initially, the researchers drove the tractors at the same speed to start the unloaded test, then gradually reduced the rear tractor's speed to place the tested tractor under load. They determined the maximum load as the point at which the tested tractor struggled to pull the rear tractor and slowed to nearly a stop. In the third stage, the researchers removed the tow rope between the tractors and drove the tested tractor alone at its maximum speed.

The highest value of all measurements taken at each stage indicates the measurement result for that stage. If the maximum noise level measured in all three stages is below 90 dB(A), the tractor is deemed to meet the regulation requirements, and the test is completed.

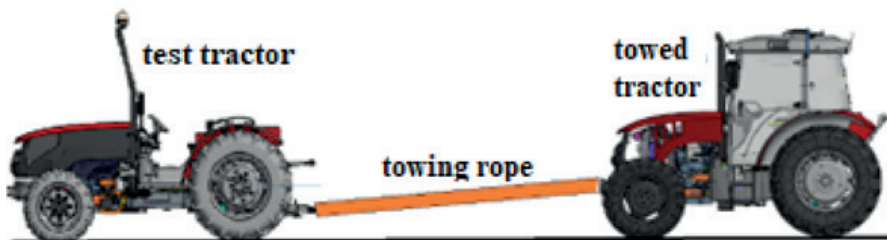


Figure 2. Test method one measurement setup

Test Method 2. The researchers repeat each noise measurement three times and record each measurement for 10 seconds. If the tractor being tested has a protective cab structure, they perform the first series of measurements with all openable doors and windows closed. For the second series, the researchers open the doors and windows during testing if doing so does not compromise road safety; if they cannot open the doors and windows, the researchers keep the front windows closed.

The noise level reaching the driver’s ear is measured at the gear position that comes when the tractor is travelling at a speed closest to 7.5 km/h, which is the design speed, at nominal rpm. The noise levels on the driver’s right and left sides are measured separately and recorded.

The testing team considers the tractor to meet regulatory requirements if the noise levels measured in both series are below 86 dB(A) and concludes the test.

3. RESULTS AND DISCUSSION

All five tractors tested reached the speed closest to 7.5 km/h in the field-fast-3 gear combination. The researchers selected this gear position based on the speed table calculated using the motor wheel ratio and nominal motor speed. They used this gear position in both test methods. In Method 1, during the first stage, the researchers loaded the tractor in three stages while it was in the field-fast-3 gear and took recordings. In the second stage, they loaded the tractor in stages while it was in the field-slow-3 gear, took three recordings, and then proceeded to the next step. In the third stage, they used the road-fast-4 gear to measure the noise level the driver experienced at maximum speed and took two recordings. The researchers present the test results in Table 2.

Table 2. Test Method 1 Measurement Results dB(A)

Tractor Name	Step 1	Step 2	Step 3	Result
Tractor A	85.2	86.7	86.1	87.7
	85.6	87.6	86.4	
	86.1	87.7	-	
Tractor B	88.0	89.1	89.4	89.5
	88.1	89.2	89.5	
	88.2	89.4	-	
Tractor C	83.9	84.7	84.3	86.4
	84.6	85.7	84.4	
	85.4	86.4	-	

Tractor Name	Step 1	Step 2	Step 3	Result
Tractor D	86.6	87.5	86.5	89.5
	87.9	88.8	86.7	
	88.3	89.5	-	
Tractor E	85.5	86.5	85.3	89.8
	86.5	87.8	86.2	
	87.3	89.8	-	

The researchers calculated the results of the tractors tested under Method 1 conditions as percentages of their proximity to the 90 dB(A) limit value. The results were as follows: Tractor A: 2.56%; Tractor B: 0.56%; Tractor C: 4.00%; Tractor D: 0.56%; and Tractor E: 0.22%. During testing under load, the researchers recorded the highest noise level in Tractor E, which uses Engine Type 3. Tractor B and Tractor D, which use Engine Type 2, are very close to the limit value. Tractor A and Tractor C, which use Engine Type 1, performed better than the other tractors under load.

Under Method 2, the researchers measured the noise level reaching the driver's ear at the Field-Fast-3 gear, which provides a speed closest to 7.5 km/h, for five tractors. The test results are presented in Table 3. All tractors are below the limit value of 86 dB(A) specified in Annexe XIII of EU Regulation 1322/2014.

Table 3. Test Method 2 Measurement Result dB(A)

Tractor Name	Left Side dB(A)	Right Side dB(A)	Result dB(A)
Tractor A	86.0	85.5	86.0
	85.9	85.4	
	85.9	85.1	
Tractor B	84.7	85.1	85.1
	84.6	84.6	
	84.8	84.7	
Tractor C	86.0	85.5	86.0
	85.9	85.4	
	85.9	85.1	
Tractor D	84.7	84.8	84.9
	84.9	84.8	
	84.8	84.6	

Tractor Name	Left Side dB(A)	Right Side dB(A)	Result dB(A)
Tractor E	85.5	85.9	85.9
	85.7	85.9	
	85.6	85.8	

When evaluating the test results for tractors, their proximity to the limit value of 86 dB(A) for method two was checked and calculated as a percentage. The results are as follows: Tractor A: 0%; Tractor B: 1.05%; Tractor C: 0%; Tractor D: 1.28%; and Tractor E: 0.12%. In this test method applied without load, it is observed that Tractor A and Tractor C, which use Engine Type 1, have noise levels exactly at the limit value. Tractor E, which uses Engine Type 3, is very close to the limit value. Tractor B and Tractor D, which use Engine Type 2, were found to produce lower noise levels than the others when unloaded.

4. CONCLUSIONS

There are many sources of noise in tractors, such as the engine, cooling fan, transmission, exhaust system, and metal parts that transmit noise through vibration. The five tested tractors have similar transmissions and body structures; this indicates that the differences in noise levels are due to variations in the engine, cooling fan and exhaust systems, as well as differences in engine operating characteristics.

When tractors equipped with engine two were tested using test method 2, the proximity of the noise level generated to the limit value was 1.05% for tractor B, and 1.28% in Tractor D, while in test method one, conducted under load, the proximity of the noise levels generated by both tractors to the limit value was 0.56%.

Tractor E, which uses Engine Type 3, obtained results very close to the limit values in both the loaded and unloaded test methods, at 0.22% and 0.12%, respectively.

Tractor A and Tractor C, which use Engine Type 1, obtained results at the full limit value in unloaded test method 2, while in method 1, which was performed under load, the measured noise level was close to the limit value, at 2.56% for Tractor A and 4.00% for Tractor C. These two tractors performed better than the other tractors. Additionally, the researchers found that using Engine Type 1 in the tested transmission and body reduced noise under load compared to the no-load condition. They also found that, because engine speed decreases with increasing load, the cooling fan accounts for a significant portion of the

noise. Reducing the fan speed or using a fan with a lower noise level and a different blade design and configuration will reduce the noise level reaching the driver's ears and make the tractor more ergonomic (Celen and Arin, 2003).

According to Method 1, the noise level ranking of tractors is Tractor E > Tractor B = Tractor D > Tractor A > Tractor C. According to Method 2, the noise ranking of tractors is Tractor A = Tractor C > Tractor E > Tractor B > Tractor D.

When evaluating results, given that farmers generally use tractors under load in field work, selecting a tractor with Engine Type 1 indicates they will be exposed to lower noise levels because this motor generates less noise when loaded.

In addition, while measurement methods allow us to observe tractor characteristics under different conditions, testing has shown that manufacturers generally prefer method 2 in type-approval tests due to its labour-intensive nature, longer test times, and greater equipment requirements.

For example, in method 2, the test is completed in a single stage, whereas in method 1, it is performed in three phases. In Method 2, the researchers note that measuring at a gear ratio other than 7.5 km/h may produce higher noise levels, but they do not account for this. Additionally, in Method 1, the researchers find that identifying the gear producing at least 1 dB more noise in the second stage complicates the test process. They conduct the test in Method 1 only at 7.5 km/h and reduce the limit value from 90 dB to 89 dB. Furthermore, Method 1, measuring the noise level at maximum speed in the third stage may pose a safety risk while driving. For this reason, the third stage, which typically yields a lower dB value, can be omitted from Method 1.

This study clearly shows that test method one needs improvement. To provide better suggestions for improving test method 1, more studies should be conducted.

5. ENGINEERING RECOMMENDATIONS AND FUTURE IMPROVEMENTS

Based on the findings of this study, several engineering recommendations can be proposed:

1. Cooling fan optimization should be prioritized
 - o Variable speed fan systems
 - o Optimized blade geometry

- o Reduced aerodynamic noise
- 2. Engine calibration strategies should consider noise-performance trade-offs
 - o Lower idle and nominal speeds
 - o Optimized combustion timing
- 3. Cabin insulation improvements
 - o Use of composite materials
 - o Isolation of vibration paths

From a regulatory perspective, a hybrid test methodology combining the repeatability of Method 2 with the realism of Method 1 would provide more accurate assessments.

Future studies should focus on:

- Long-term operator exposure
- Field-condition variability
- Correlation between lab tests and real usage

6. CRITICAL EVALUATION OF TEST METHODS

A critical comparison of the two test methods reveals significant methodological differences that affect both accuracy and applicability.

Test Method 1 aims to simulate real operating conditions by introducing load. However, the lack of standardisation in load application introduces variability. The use of a towing tractor and rope-based loading system may lead to inconsistencies in applied load and repeatability issues.

In contrast, Test Method 2 provides a highly controlled and repeatable testing environment. However, it fails to represent real agricultural usage, where tractors predominantly operate under load.

Another important limitation of Method 1 is the requirement to identify a gear that produces at least 1 dB(A) higher noise. This condition introduces ambiguity and may lead to operator-dependent variability in test execution.

Moreover, the third stage of Method 1, which involves testing at maximum speed, has limited relevance to typical agricultural operations and may introduce unnecessary safety risks.

Overall, Method 2 offers better repeatability and practicality, while Method 1 provides better representation of real-world conditions. However, neither method alone fully captures the operational noise exposure experienced by tractor operators.

7. DETAILED ANALYSIS OF NOISE SOURCES

The noise measured at the driver's ear is a superposition of multiple acoustic sources, including combustion noise, mechanical vibration, intake and exhaust flow noise, and cooling system components.

In the tested tractors, since transmission and chassis structures are similar, the primary differences arise from:

- Engine combustion characteristics
- Cooling fan design and speed
- Exhaust aftertreatment configuration (DOC, DPF, SCR)

One of the most critical findings of this study is the influence of engine load on cooling fan behaviour. Under loaded conditions, engine speed tends to decrease, which directly reduces fan rotational speed. As a result, fan-induced noise—one of the dominant contributors at high engine speeds—becomes less significant.

Conversely, under no-load conditions, engines operate at higher speeds, increasing aerodynamic noise generated by the cooling fan. This explains why some tractors exhibit worse performance in Method 2 despite performing better under load.

Additionally, exhaust aftertreatment systems such as DPF and SCR may introduce flow resistance and acoustic damping effects. However, their contribution to overall noise levels is secondary compared to fan and combustion noise.

8. REGULATORY FRAMEWORK AND ENGINEERING IMPLICATIONS

The driver exposure noise limits defined under EU Regulation 167/2013 and EU Regulation 1322/2014 are not only a compliance criterion but also a design input.

The noise limits defined in Annexe XIII are not only compliance thresholds but also critical engineering constraints that directly influence tractor design. In particular, the differentiation between 90 dB(A) for Test Method 1 and 86

dB(A) for Test Method 2 introduces a dual evaluation framework that may lead to different design optimization strategies.

From an engineering perspective, manufacturers tend to optimize their products according to the test method most frequently used in type-approval procedures. As observed in this study, Test Method 2 is generally preferred due to its simplicity and repeatability. This preference may unintentionally lead to suboptimal acoustic performance under real operating conditions, especially under load.

Furthermore, the regulatory structure does not explicitly enforce correlation between the two methods. This creates a potential gap between laboratory-based compliance and real-world operator exposure. Therefore, it is essential to evaluate whether current regulatory limits sufficiently represent actual usage scenarios in agricultural operations.

9. EXTENDED METHODOLOGICAL EVALUATION

The methodology applied in this study follows the requirements defined in EU Regulation 1322/2014. However, beyond regulatory compliance, it is essential to evaluate the robustness, repeatability, and engineering validity of the applied procedures.

One of the most critical aspects of the methodology is the selection of the gear corresponding to the design speed of 7.5 km/h. This selection directly affects engine operating conditions, including engine speed, torque demand, and consequently noise generation. Although the regulation specifies this speed, tractors in real agricultural operations rarely operate continuously at a fixed speed. Therefore, limiting the analysis to a single operating point may not fully represent real-world usage.

Another important methodological factor is the load application technique used in Test Method 1. In this study, load was applied using a towing tractor connected via a rope system. While this approach is practical, it introduces several uncertainties:

- Difficulty in maintaining a constant and measurable load level
- Variability depending on operator control
- Lack of precise load quantification

From an experimental engineering perspective, the absence of a controlled dynamometric system reduces measurement repeatability. Future studies should consider the use of dynamometers or controlled braking systems to ensure more accurate load application.

In addition, environmental conditions such as wind speed, ground roughness, and ambient noise may influence measurements. Although the regulation requires these factors to be minimized, complete elimination is not possible in open-field testing environments. This introduces a level of uncertainty that should be acknowledged when interpreting results.

Finally, microphone positioning plays a critical role in measuring accuracy. Small deviations in position relative to the driver's ear can result in measurable differences in recorded noise levels. Therefore, strict adherence to positioning requirements is essential for ensuring consistency across tests.

10. STATISTICAL INTERPRETATION OF RESULTS

Although the results are presented as maximum values in compliance with regulatory requirements, a deeper statistical interpretation provides additional insights into tractor noise behaviour.

For each tractor, multiple measurements were taken under different stages and conditions. Instead of focusing solely on maximum values, evaluating the distribution of measurements allows for better understanding of variability and stability.

For example, tractors with narrow variation ranges between repeated measurements indicate more stable acoustic behaviour, while larger variations suggest sensitivity to operating conditions.

In this study:

- Tractor C exhibited relatively stable measurements across all stages
- Tractor D showed higher variability, particularly under load
- Tractor E consistently produced high values close to the limit

These observations indicate that not only peak noise levels but also consistency should be considered in evaluating tractor performance.

Furthermore, the percentage proximity to limit values provides a useful comparative metric. However, this metric alone may be misleading. For example, a tractor operating consistently near the limit may pose a greater long-term risk than one that occasionally reaches high values.

A more comprehensive evaluation could include:

- Standard deviation of measurements
- Confidence intervals
- Time-weighted exposure levels

Such statistical approaches would significantly enhance the scientific strength of the study.

11. OPERATIONAL SCENARIO ANALYSIS

One of the key limitations of current regulatory testing procedures is the lack of representation of real agricultural operating scenarios.

In actual field conditions, tractors operate under highly variable loads depending on:

- Soil conditions
- Implement type (plough, seeder, trailer)
- Terrain slope
- Operator behaviour

Unlike the controlled conditions of Test Method 2, real-world operations involve continuous fluctuations in engine load and speed. This results in dynamic changes in noise levels, which are not captured by steady-state measurements.

Test Method 1 attempts to address this limitation by introducing load. However, the loading method used does not fully replicate real implement-based loading conditions. For example, pulling another tractor creates a different load profile compared to soil-engaging implements.

Additionally, transient conditions such as acceleration, deceleration, and gear shifting are not considered in either test method. These transient events can produce short-term noise peaks that may significantly affect operator exposure.

From an occupational health perspective, continuous exposure to fluctuating noise levels may have different effects compared to steady noise exposure. Therefore, future test procedures should consider integrating dynamic test cycles similar to those used in emission testing (e.g., NRSC, NRTC).

12. EXPANDED ENGINEERING DISCUSSION

The findings of this study highlight the strong relationship between engine characteristics and noise performance. Engine Type 1 demonstrated better performance under loaded conditions. This suggests that its combustion characteristics and torque delivery are more favourable in terms of acoustic output. Lower engine speeds under load reduce both combustion frequency and cooling fan noise. In contrast, Engine Type 2 performed better under no-load conditions. This indicates that its design may be optimised for higher

speed efficiency rather than load-dependent performance. Engine Type 3, despite having lower rated power, produced noise levels close to the limit in both methods. This suggests that factors such as engine balance, cylinder configuration, and vibration characteristics play a significant role.

Cooling fan behaviour emerges as a dominant factor across all engines. Since fan speed is directly proportional to engine speed, noise generated by the fan increases significantly at higher rpm levels. Therefore, implementing variable-speed or electronically controlled fans could significantly reduce noise levels.

Another important factor is structural vibration transmission. Even if the primary noise source is the engine, the way vibrations are transmitted through the chassis and cabin structure determines the final noise level at the driver's ear.

13. LIMITATIONS OF THE STUDY

This study provides a comparative evaluation of two noise test methods defined in Annexe XIII of EU Regulation 1322/2014; however, several limitations should be considered when interpreting the results.

First, the number of tractors included in the study is limited to five prototypes. Although these tractors were selected to represent different engine configurations, the sample size is not sufficient to generalize the findings across all agricultural tractor categories. Variations in tractor design, including cabin structure, insulation materials, and transmission systems, may influence noise characteristics and are not fully represented in this study.

Second, the load application method used in Test Method 1 is based on a towing approach, where a second tractor provides resistance through a rope connection. While this method enables practical implementation under field conditions, it does not allow precise quantification or control of the applied load. Consequently, variations in operator behaviour and environmental conditions may introduce inconsistencies in the measurements. The absence of a controlled dynamometric system limits the repeatability and accuracy of the results.

Another limitation is related to the operating conditions considered in the tests. Both test methods are conducted at a fixed target speed of approximately 7.5 km/h, as specified in the regulation. However, real agricultural operations involve a wide range of speeds, loads, and transient conditions such as acceleration, deceleration, and gear shifting. These dynamic effects are not captured in the current testing procedures, which may result in differences between measured values and actual operator exposure.

In addition, environmental factors such as wind speed, ground surface conditions, and ambient noise levels may influence the measurements, despite efforts to minimize their effects. Field testing inherently includes uncertainties that cannot be entirely eliminated, and these should be considered when evaluating the results.

Furthermore, the study focuses on short-term noise measurements rather than long-term exposure. Occupational health risks associated with noise are typically related to cumulative exposure over extended periods. Therefore, the findings of this study do not fully reflect the long-term impact of tractor noise on operators.

Finally, although the study compares two regulatory test methods, it does not establish a direct correlation between laboratory-based measurements and real-world noise exposure. Future research should aim to bridge this gap by incorporating long-duration field measurements and more representative loading conditions.

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CHAPTER 4

The Effect of Engine and Transmission Type on Specific Fuel Consumption and Carbon Emissions in Stage V Tractors

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ABSTRACT

Energy efficiency in agricultural mechanization is crucial for cost management and environmental sustainability. This study empirically investigates the interaction of specific fuel consumption (SFC) with engine architecture, transmission configuration, and nominal engine speed in tractors compliant with the European Union Stage V emission standards. The research material consists of technical data from 34 different tractor models tested by the Agricultural Implements and Machinery Test Center Directorate (TAMTEST) in Ankara in accordance with international OECD Code 2 protocols. Within the scope of the analysis, six different transmission types and four main engine technologies (A, D, E, K) were evaluated comparatively. The empirical findings demonstrate that the selection of engine and drivetrain components plays a decisive role in energy efficiency. Among the four analyzed engine types, the E-type engine exhibited the most optimized specific fuel consumption performance at 267.4 g/kWh, whereas the D-type engine recorded the highest consumption value at 298.167 g/kWh. On the transmission side, B-type systems were identified as providing higher transmission efficiency

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compared to other configurations. The estimations conducted in this study reveal the macroeconomic and ecological potential that would emerge if the most efficient unit among the examined engine types (E-type) were to replace the least efficient unit (D-type). Calculations based on Turkey's approximately 1.6-million-unit tractor fleet indicate that such technological optimization could result in hourly fuel savings of 2.63 million liters and a reduction of approximately 7.02 million kg of CO₂ emissions. When extrapolated to the global tractor population of 50 million units, this potential corresponds to hourly fuel savings of 81.44 million liters and a CO₂ emission reduction of 218.26 million kg. In conclusion, this study demonstrates that engine and transmission optimization directly reduces the carbon footprint, supporting sustainable agricultural policies.

Keywords: Stage V Emission, Specific Fuel Consumption (SFC), Transmission Efficiency Engine Characterization OECD Code 2, Sustainable Agriculture

INTRODUCTION

The agricultural sector is a continuously evolving field driven by the need to meet the growing global demand for food. Within this development, agricultural machinery particularly tractors play a critical role. However, the widespread use of agricultural machinery also entails significant environmental impacts. Exhaust emissions from diesel-powered tractors have a substantial influence on air quality and climate change. Consequently, emission standards and fuel efficiency have become increasingly important considerations in the agricultural machinery sector (Gil-Sierra et al., 2007). Exhaust emissions adversely affect air quality and contribute directly to climate change (Fontaras et al., 2019).

As of early 2025, the number of tractors in Türkiye has reached 1,598,659 units (T.C. Tarım ve Orman Bakanlığı, 2025). At the global scale, more than 50 million agricultural tractors are estimated to be in operation worldwide (Market Reports World, 2025). Fuel efficiency in agriculture is a key component not only of operational cost management but also of environmental sustainability. Tractor fuel consumption depends on multiple factors, including engine technology, transmission systems, and overall design characteristics (Serrano et al., 2007). Improvements in fuel efficiency have multidimensional effects on economic costs, energy security, and environmental sustainability. Reduced fuel consumption directly results in lower greenhouse gas emissions, particularly carbon dioxide (CO₂). In the literature, the amount of CO₂ released from the combustion of one liter of diesel fuel is calculated using the internationally accepted emission factor of 2.67 kg/L (IPCC, 2006).

In recent years, increasingly stringent regulations have been introduced worldwide to reduce pollutant emissions from agricultural machinery. This regulatory process began with the implementation of Stage I standards by the European Union in 1999 and progressed through successive transitions to Stage II, III, and IV, gradually lowering emission limits. The currently enforced Stage V emission standards represent the most recent and stringent requirements for tractor engines (OECD, 2023).

Designed primarily to minimize nitrogen oxides (NO_x) and particulate matter (PM) emissions from diesel engines, Stage V standards are now applied across a broad geographical area, particularly in Europe and North America (Fontaras et al., 2019). Similarly, in Türkiye, Stage V engine technology has rapidly become established in the modern tractor and non-road machinery market, and the existing machinery fleet is being progressively modernized to comply with these high standards (Duran et al., 2024). This technological evolution from Stage I to Stage V has resulted in reductions exceeding 90% in PM and NO_x emissions (Serrano et al., 2018).

Fuel efficiency in the agricultural sector is of critical importance from both environmental sustainability and operational cost perspectives. The fuel consumption of tractors used in modern agricultural practices is influenced by numerous factors, including engine technologies, transmission systems, and general design features (Rinaldi et al., 2018). Today, energy efficiency and fuel consumption are key issues not only for agricultural machinery such as tractors but also for passenger vehicles (Mermer, 2025).

This significance arises from multidimensional considerations, including environmental sustainability, economic costs, and energy security. The consumption of fossil fuels intensifies global environmental problems by increasing greenhouse gas emissions and accelerating climate change. In this context, improving vehicle fuel efficiency has become a strategic objective for reducing carbon footprints and enhancing air quality.

As with passenger vehicles, fuel consumption in tractors has substantial economic and environmental implications. From an economic standpoint, fuel costs constitute one of the largest expenditure items in agricultural enterprises. Tractors with lower fuel consumption enable farmers to reduce operating costs and improve profitability. In large-scale agricultural operations, even marginal improvements in fuel efficiency can yield significant long-term savings. From an environmental perspective, fuel consumption is directly associated with greenhouse gas emissions. Consequently, increasing fuel efficiency in tractors is a fundamental component of sustainable agricultural practices (Mermer, 2025).

The Stage V emission standards established by the European Union impose stricter emission limits for non-road mobile machinery (NRMM). These standards specifically target reductions in particulate matter (PM) and nitrogen oxide (NOx) emissions (International Council on Clean Transportation, 2016). To comply with Stage V requirements, engine manufacturers employ advanced exhaust after-treatment systems such as diesel particulate filters (DPF) and selective catalytic reduction (SCR). These technologies can have a direct impact on engine performance and fuel consumption.

Internationally recognized test procedures are available to evaluate tractor performance and fuel consumption. The OECD Code 2 test procedures, developed by the Organization for Economic Co-operation and Development (OECD), are used to measure tractor power output, fuel consumption, and other performance parameters under standardized conditions (OECD, 2025). Specific fuel consumption (SFC) is a key performance indicator expressing the amount of fuel consumed per unit of power output and is widely used to compare tractor energy efficiency. Since 1965, the OECD has established standardized testing codes for agricultural tractors, which have been adopted by member countries to ensure consistent and reliable performance assessment (Stayner, 1988).

The Agricultural Machinery Testing Center Directorate (TAMTEST) was established in 1962 and is responsible for conducting tractor and agricultural machinery tests in Türkiye in accordance with OECD criteria. Test results are documented in detailed reports, and when required, OECD approval is obtained to ensure international validity across member countries (T.C. Tarım ve Orman Bakanlığı, 2024).

In this study, the effects of engine and tractor type characteristics on fuel consumption performance of Stage V compliant tractors are examined in detail. The analyses reveal how different engine types, tractor categories, and nominal engine speeds influence fuel consumption behavior. The findings aim to provide a scientific basis for informed tractor selection by stakeholders in the agricultural sector and for optimizing fuel efficiency in future tractor designs. Additionally, by evaluating emission reduction potential, the study seeks to contribute to the development of sustainable solutions within the agricultural sector (Yumrukaya & Karakaş, 2025).

MATERIALS AND METHODS

In this study, a comprehensive dataset was utilized to evaluate the fuel consumption performance of tractors compliant with Stage V emission standards. The dataset includes engine and transmission specifications, nominal

engine speeds, and specific fuel consumption (SFC, g/kWh) values of tractor models marketed under different commercial brands. The data comprises 34 distinct tractor types, six different transmission manufacturers (A, B, C, D, E, F), and engines belonging to four regulatory families (D, E, A, K), which are grouped and summarized in Table 1.

This level of diversity provides a robust analytical framework for assessing the influence of different tractor configurations on fuel consumption behavior.

Table 1. Classification of Tested Tractors

Transmission Type	Gear Ratios	Engine Type
A Tip	16+16 / 16+8 PS	D / E
B Tip	24+24 / 12+12	D / A / E
C Tip	16+16	K / D / A / E
D Tip	12+12 / 8+8	K
E Tip	16+16 / 16+8	K / D / A
F Tip	8+8	K

OECD Code 2 (Organisation for Economic Co-operation and Development Standard Code for the Official Testing of Agricultural and Forestry Tractor Performance) is an internationally recognized testing standard developed to evaluate the performance and reliability of agricultural tractors. Introduced by the OECD in 1965, this code established harmonized tractor testing procedures among member countries.

Through this standardization, tractor fuel consumption and performance characteristics tested or manufactured in different countries can be assessed using objective and directly comparable data. OECD Code 2 tests determine critical performance parameters such as specific fuel consumption under defined load and engine speed conditions, thereby enhancing transparency and reliability within the agricultural machinery sector. The data obtained from these tests not only guide manufacturers during product development processes but also provides farmers with scientifically grounded information to support informed purchasing decisions.

Specific fuel consumption values were examined individually for each tractor model, and their relationships with engine type, transmission characteristics, and nominal engine speed were systematically investigated. To facilitate interpretation, tables and graphical visualizations were generated. These visual tools aim to clearly reveal fuel consumption trends and differences among various tractor models.

Each tractor's SFC value was evaluated in conjunction with its corresponding engine and transmission configuration. Accordingly, engine types and transmission layouts associated with relatively lower or higher fuel consumption levels were identified. Furthermore, the potential influence of nominal engine speed on fuel consumption was also examined. The findings obtained from this analysis are expected to contribute to the development of strategies aimed at improving fuel efficiency in the agricultural machinery sector.

2.1. Research Material

The primary research material consists of technical test reports of 34 different tractor models tested in accordance with OECD Code 2 protocols (Standard Code for Measuring the Power of Agricultural and Forestry Tractor Power Take-Off Shafts). All tractors included in the study are equipped with Stage V technology, representing the most recent emission regulation. Based on their technological configurations, the tractors were categorized according to four engine types (A, D, E, K) and six transmission types.

The nominal power ranges and engine characteristics of the tested tractors exhibit sufficient variability to represent the existing tractor fleet.

2.2. Experimental Method and Data Collection

The experimental procedure comprised dynamometer tests conducted to evaluate the power take-off (PTO) performance of the tractors. During the tests, engine speed, torque output, and hourly fuel consumption were recorded simultaneously. Specific fuel consumption (SFC), defined as the amount of fuel consumed per unit of power output, was considered a primary indicator of energy efficiency.

The mathematical model used to calculate SFC is presented in Equation (1):

$$SFC = \frac{B}{P} \quad (1)$$

where:

SFC = specific fuel consumption (g/kWh)

B = hourly fuel consumption (g/h)

P = net power output measured at the PTO shaft (kW)

2.3. Emission Reduction Projection

To quantify the environmental impacts associated with changes in engine type, a simulation model was developed based on the tractor populations in Türkiye and worldwide. In this model, the difference in SFC between the most fuel-efficient and the least fuel-efficient engine types was converted into potential fuel savings.

The carbon dioxide (CO₂) equivalent of the calculated fuel savings was determined using the internationally accepted emission factor of 2.67 kg/L [13], as presented in Equation (2). A total tractor population of 1,598,659 units for Türkiye and 50 million units for the global tractor fleet were used as the basis for the calculations.

$$CO_2 \text{ Reduction (million kg/hour)} = SFC \times 2.67 \text{ kg/L} \quad (2)$$

2.4. Statistical Methods

Analysis of variance (ANOVA) was employed to determine the effects of engine and transmission types on specific fuel consumption. Statistical differences among groups were evaluated using Duncan’s Multiple Range Test at a significance level of $P < 0.05$. All statistical analyses and graphical representations were performed using standard statistical software packages.

Table 2. Engine and transmission classification of tractors evaluated in the study

Engine Type	Number of Tractors	Transmission Type
A Tipi	8	A, B, C
D Tipi	10	B, D, E
E Tipi	9	A, C, F
K Tipi	7	D, E, F

3. THE RESEARCH FINDINGS AND DISCUSSION

The analysis conducted revealed that engine architecture and transmission configuration have a statistically significant effect on specific fuel consumption (SFC) in tractors compliant with Stage V emission standards ($P < 0.05$).

3.1. Specific Fuel Consumption According to Transmission Types

Table 3 lists the transmission systems of six different manufacturers according to the tractor models in which they are used.

Table 3. Average Specific Fuel Consumption and Power at Rated Engine Speed by Transmission Type

Test Value					
Type	Commercial Representation	Engine	Gear Ratio	Power at Rated Speed (kW)	SFC at Rated Speed (g/kWh)
A	7 tractors	D and E	16+8 / 16+16	60.20	312.50
B	10 tractors	D/A/E	24+24 / 12+12	52.90	269.30
C	6 tractors	K/D/A/E	16+16	45.23	294.83
D	5 tractors	K	12+12/8+8	34.12	284.00
E	4 tractors	K/D/A	16+8 / 16+16	42.72	290.25
F	2 tractors	K	8+8	32.60	275.50

The analysis conducted based on transmission types similarly revealed notable differences in fuel consumption. The Type B transmission exhibited the lowest average specific fuel consumption at 269.3 g/kWh, whereas the Type A transmission showed the highest average value at 312.5 g/kWh. The remaining transmission types of Type C, Type D, Type E, and Type F recorded average SFC values of 294.83 g/kWh, 284.0 g/kWh, 290.25 g/kWh, and 275.5 g/kWh, respectively. These results demonstrate that the gear ratios and overall efficiency of the transmission system play a critical role in determining fuel consumption. Particularly in agricultural applications, appropriate gear ratio selection and efficient transmission operation are of paramount importance for achieving fuel savings.

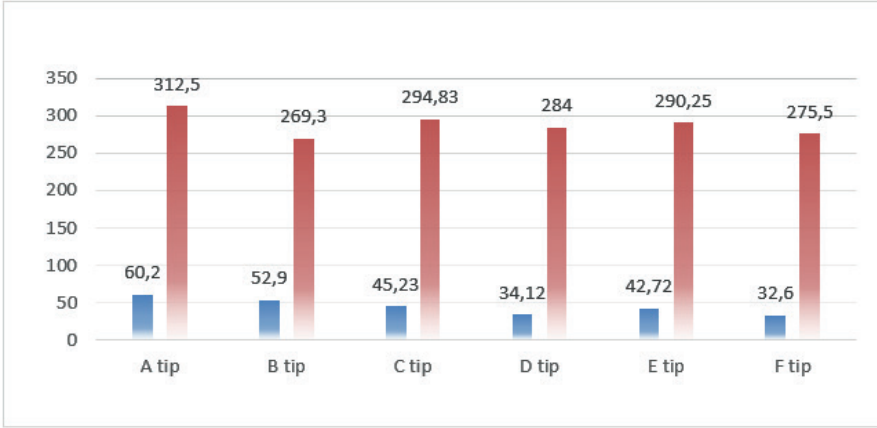


Figure 1. Average Specific Fuel Consumption by Transmission Type

3.2. Specific Fuel Consumption According to Engine Types

An examination of the average specific fuel consumption values by engine type indicated that certain engine configurations are more efficient than others. Specifically, the E-type engine exhibited the lowest average SFC value at 267.4 g/kWh, while the D-type engine showed the highest average value at 298.17 g/kWh. The A-type and K-type engines fell between these two extremes, with average SFC values of 283.29 g/kWh and 285.67 g/kWh, respectively. These findings indicate that differences in engine technology have a direct impact on fuel efficiency. Manufacturers may enhance overall performance by prioritizing engine selection based on fuel economy considerations during the design phase.

It was calculated that the E-type engine consumes 30.77 g/kWh less fuel per tractor compared to the D-type engine. Considering that the average rated power of the 34 tested tractors at nominal engine speed is 45 kW, and that there were 1,598,659 tractors in Türkiye at the beginning of 2025 [3], the hourly fuel savings achieved by replacing the least efficient engine type with the most efficient one among the four type-approved engine categories were calculated using Equation (3). The results indicate a potential fuel saving of 2,603,961.61 L/h.

$$F = \frac{AxBxD}{Cx E} \quad (3)$$

where:

A = reduction in fuel consumption per tractor (g/kWh)

B = number of tractors

C = conversion coefficient from grams to kilograms

D = average rated power at nominal engine speed (kW)

E = fuel density (kg/L)

F = fuel saved per hour (L/h)

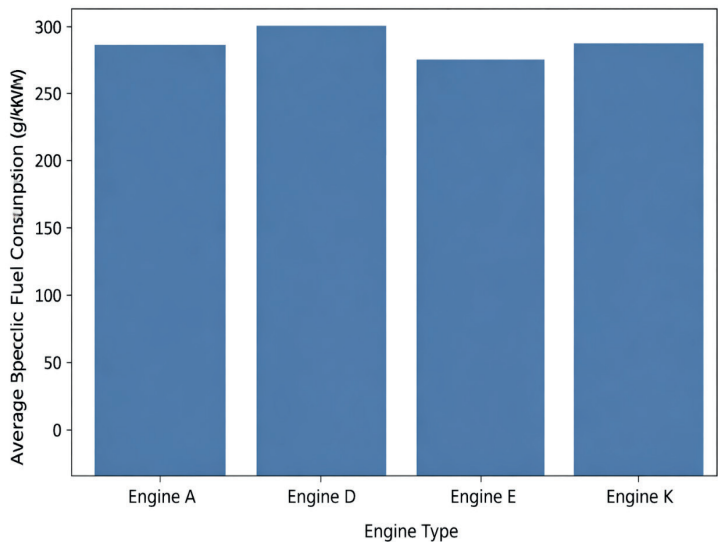


Figure 2. Average Specific Fuel Consumption by Engine Type

3.3. Relationship Between Rated Engine Speed and Specific Fuel Consumption

An analysis of the relationship between rated engine speed and specific fuel consumption revealed that, in general, fuel consumption decreases by increasing engine speed up to a certain point, after which it may increase again. This behavior indicates the existence of an optimal operating speed range in which engines achieve maximum efficiency, while fuel efficiency declines outside this range. Operating tractors at optimal engine speeds under field conditions can therefore yield substantial benefits in terms of fuel economy.

3.4. Effect of Engine Type and Transmission Configuration on SFC

Among the 34 tractor models examined, E-type engines demonstrated the highest level of energy efficiency. The average SFC values obtained for each engine type are presented in Table 4.

Table 4. Average specific fuel consumption values by engine type

Engine Type	Average SFC (g/kWh)	Standard Deviation
E	267.40	12.45
A	278.15	15.20
K	285.90	11.80
D	298.17	14.65

The findings indicate that the E-type engine is approximately 10.3% more efficient than the D-type engine. This difference is attributed to advancements in fuel injection systems and combustion chamber optimization.

3.5. National and Global Fuel Savings and CO₂ Emission Reduction Projection

One of the most significant findings of this study is the macro-scale environmental impact of technological optimization, specifically the transition from D-type to E-type engines. Hourly calculations based on national and global tractor fleets are detailed in Table 5. CO₂ emissions were calculated according to Equation (2).

Table 5. Hourly fuel savings and CO₂ emission reductions achievable through engine optimization

Scale	Number of Tractors	Fuel Savings (million L/h)	CO ₂ Reduction (million kg/h)
Türkiye	1.598.659	2.63	7.02
Global	50.000.000	81.44	217.44

Based on the emission factor of 2.67 kg/L used in the calculations (Rinaldi et al., 2019), the fact that all tractor engines evaluated in this study comply with the European Union Stage V emission legislation clearly indicates that the observed differences in CO₂ emissions are not attributable to regulatory

compliance, but rather to technical differences in engine architecture and transmission configurations. The Stage V regulation defines limit values for pollutant emissions such as NO_x, PM, and PN for NRMM engines, but does not directly regulate CO₂ emissions. Accordingly, the calculated hourly CO₂ reduction potential of 7.02 million kg for the Turkish tractor fleet demonstrates that significant efficiency differences in terms of specific fuel consumption can exist even among engines that fully comply with Stage V requirements. Similarly, the global reduction potential of 217.44 million kg CO₂ per hour suggests that technical optimizations in powertrain systems extend beyond current EU NRMM legislation and exhibit an indirect yet measurable alignment with the EU's long-term CO₂ reduction roadmaps.

3.6. Discussion

The findings of this study provide a comprehensive evaluation of the relationship between engine architecture, transmission configuration, and specific fuel consumption (SFC) in Stage V-compliant agricultural tractors. The results demonstrate that fuel efficiency is governed by a complex interaction of thermodynamic, mechanical, and operational factors rather than a single design parameter.

One of the most significant outcomes of this study is the superior performance of E-type engines in terms of fuel efficiency. This result can be primarily attributed to advancements in combustion optimization, including improved fuel injection strategies, higher injection pressures, and more efficient air–fuel mixing. These factors contribute to enhanced thermal efficiency and reduced specific fuel consumption. In contrast, the relatively higher SFC values observed in D-type engines suggest less optimized combustion characteristics or higher internal energy losses.

Beyond combustion efficiency, mechanical losses within the powertrain also play a crucial role. The analysis of transmission types revealed that Type B configurations consistently produced lower SFC values compared to other transmission systems. This indicates that transmission efficiency—through optimized gear ratios, reduced friction losses, and improved torque transfer—has a direct and measurable impact on overall fuel consumption.

Importantly, the interaction between engine and transmission systems emerges as a key determinant of performance. The results suggest that even highly efficient engines may not achieve their full potential if paired with suboptimal transmission configurations. Conversely, efficient transmissions can amplify the benefits of advanced engine technologies. This highlights

the necessity of adopting a system-level optimization approach rather than focusing on individual components in isolation.

Another critical finding relates to the influence of operating conditions on fuel consumption. The observed nonlinear relationship between rated engine speed and SFC confirms the existence of an optimal operating range in which engines achieve maximum efficiency. Operating outside this range, either at excessively low or high engine speeds leads to increased fuel consumption due to incomplete combustion, higher frictional losses, or increased pumping work. This finding is consistent with previous studies reported in the literature, which emphasize the importance of load-dependent engine performance optimization.

From an environmental perspective, the results of this study reveal a significant discrepancy between regulatory compliance and actual carbon emission performance. Although all tractors evaluated comply with Stage V emission standards, substantial differences in CO₂ emissions were observed due to variations in fuel consumption. This finding underscores a critical limitation of current regulatory frameworks, which focus primarily on pollutant emissions such as NO_x and particulate matter, while indirectly addressing CO₂ emissions.

The large-scale projections presented in this study further emphasize the magnitude of this issue. The estimated fuel savings and CO₂ emission reductions at both national and global levels demonstrate that even incremental improvements in SFC can lead to substantial environmental benefits when scaled across large tractor populations. However, these projections should be interpreted with caution, as they are based on simplified assumptions regarding operating conditions and tractor utilization rates.

In addition to environmental implications, the findings also have important economic consequences. Fuel constitutes a major component of operational costs in agricultural activities, and improvements in fuel efficiency directly translate into reduced costs for farmers. Therefore, optimizing engines and transmission configurations not only contributes to sustainability goals but also enhances the economic viability of agricultural operations.

Despite the strengths of this study, the results also highlight the need for further research. Future studies should focus on evaluating tractor performance under real-field conditions, incorporating dynamic load variations and different agricultural applications. Furthermore, integrating lifecycle assessment approaches would provide a more comprehensive understanding of the environmental impacts associated with different tractor technologies.

Overall, this study demonstrates that improving fuel efficiency in agricultural tractors requires a holistic approach that integrates engine design, transmission

optimization, and operational strategies. Such an approach is essential for achieving meaningful reductions in fuel consumption and greenhouse gas emissions in the agricultural sector.

4. RESULTS

This study empirically demonstrates the effects of engine architecture and transmission type on specific fuel consumption (SFC) and, consequently, on the carbon footprint of Stage V-compliant agricultural tractors. The principal findings of the study are summarized as follows:

Technological Efficiency:

Comparative analysis of different engine configurations revealed that E-type engines exhibit the highest fuel efficiency with an average SFC of 267.40 g/kWh, whereas D-type engines show the highest fuel consumption at 298.17 g/kWh. These results indicate that optimization of engine technology alone can yield an improvement of approximately 10.3% in fuel economy

Environmental Impact (Türkiye):

Based on projections for Türkiye's tractor fleet of approximately 1.6 million units, replacing low-efficiency engines with the most efficient alternatives could result in hourly fuel savings of about 2.63 million liters. When applying the standard emission factor of 2.67 kg/L, this reduction corresponds to an avoidance of approximately 7.02 million kg of CO₂ emissions per hour.

Global Scale:

Considering the global tractor population of nearly 50 million units, the potential impact of technological transition reaches approximately 81.44 million liters of fuel savings per hour and a corresponding reduction of 217.44 million kg of CO₂ emissions. These figures confirm the critical role of agricultural mechanization in achieving global climate mitigation targets.

System Optimization:

The findings further demonstrate that fuel economy is not solely determined by engine technology. Transmission type and PTO speed ratios also exert a direct influence on SFC. In particular, the use of economy PTO modes (540E) combined with efficient transmission configurations maximizes the environmental benefits offered by Stage V engines.

In conclusion, the modernization of Türkiye's tractor fleet in accordance with Stage V emission standards would not only reduce operational costs for farmers but also provide a strategic contribution to national carbon emission

reduction objectives. Future research should focus on evaluating the dynamic load performance of these engine types under real field conditions and with different agricultural implements.

5. LIMITATIONS OF THE STUDY

This study presents a comprehensive evaluation of the effects of engine and transmission configurations on specific fuel consumption (SFC) and associated CO₂ emissions in Stage V compliant tractors. However, several limitations should be acknowledged in order to ensure accurate interpretation of the findings.

First, the dataset used in this study is based on 34 tractor models tested under standardized conditions in accordance with OECD Code 2 procedures. While this provides a high level of consistency and comparability, the sample size remains limited in representing the full diversity of the global tractor fleet. Variations in tractor design, operational applications, and manufacturer-specific technologies may influence fuel consumption behaviour beyond the scope of this dataset.

Second, the analysis is based on steady-state dynamometer test conditions. Although OECD Code 2 provides a robust framework for performance evaluation, it does not fully represent real-world agricultural operations. In actual field conditions, tractors operate under highly dynamic loads, including transient conditions such as acceleration, deceleration, and implement-induced load fluctuations. These dynamic effects may lead to deviations in fuel consumption compared to laboratory-based measurements.

Another important limitation concerns the classification of engine and transmission types. In this study, engines and transmissions are grouped into generalized categories (A, D, E, K and A–F types). While this approach enables comparative analysis, it may obscure detailed design differences such as fuel injection strategies, turbocharging systems, electronic control algorithms, and internal mechanical efficiencies. Therefore, the observed differences in SFC should be interpreted as category-level trends rather than absolute performance indicators.

Furthermore, the emission reduction projections presented in this study are based on simplified assumptions. The calculations assume that all tractors operate at nominal engine power and for equal durations, which may not reflect actual usage patterns. In practice, tractor utilization rates vary significantly depending on farm size, crop type, and regional agricultural practices. As a

result, the estimated fuel savings and CO₂ reductions should be interpreted as theoretical potential rather than precise real-world outcomes.

In addition, the study focuses exclusively on carbon dioxide (CO₂) emissions derived from fuel consumption and does not consider other pollutant emissions such as nitrogen oxides (NO_x) and particulate matter (PM), which are directly regulated under Stage V standards. Although CO₂ is a key indicator of environmental impact, a comprehensive environmental assessment would require a multi-pollutant analysis.

Finally, economic factors such as cost differences between engine and transmission technologies, maintenance requirements, and lifecycle costs are not included in the analysis. These factors may significantly influence the practical feasibility of adopting more efficient technologies in real agricultural systems.

Future research should address these limitations by incorporating larger datasets, real-field operational measurements, dynamic load cycles, and lifecycle-based environmental and economic analyses.

6. SENSITIVITY ANALYSIS OF SPECIFIC FUEL CONSUMPTION

In order to quantify the relative influence of key design and operational parameters on fuel efficiency, a sensitivity analysis was conducted focusing on engine type, transmission configuration, and rated engine speed.

The results clearly indicate that engine type is the most influential parameter affecting specific fuel consumption (SFC). The difference between the most efficient engine (E-type) and the least efficient engine (D-type) was calculated as approximately 10.3%. This variation represents a substantial efficiency gap, particularly when extrapolated to large-scale tractor fleets.

Transmission configuration also plays a critical role in determining fuel consumption. The comparison between transmission types revealed that the difference in SFC between the most efficient configuration (Type B) and the least efficient one (Type A) exceeds 16%. This finding highlights the importance of minimizing mechanical losses and optimizing gear ratio distribution within the drivetrain.

Rated engine speed exhibits a nonlinear relationship with SFC. As engine speed increases, fuel consumption initially decreases due to improved combustion efficiency. However, beyond an optimal operating range, further increases in engine speed led to higher frictional losses, increased pumping

work, and consequently higher fuel consumption. This behavior confirms the existence of an optimal engine operating zone for minimizing SFC.

From a systems engineering perspective, these results demonstrate that fuel efficiency cannot be optimized through isolated component improvements. Instead, an integrated design approach considering the interaction between engine characteristics and transmission efficiency is required.

Furthermore, the sensitivity analysis shows that improvements in high-impact parameters, particularly engine efficiency, can result in disproportionately large reductions in fuel consumption and CO₂ emissions when applied at the fleet level. This amplification effect underscores the importance of targeted technological optimization strategies.

7. IMPLICATIONS FOR TRACTOR DESIGN AND AGRICULTURAL POLICY

The findings of this study provide important insights for both tractor manufacturers and policymakers involved in agricultural mechanization and environmental regulation.

From an engineering design perspective, the results emphasize the critical role of engine selection in determining overall fuel efficiency. The superior performance of E-type engines suggests that advancements in combustion system design, fuel injection technology, and thermal management significantly contribute to reducing SFC.

In addition to engine optimization, transmission design must be considered a key component of system efficiency. The lower SFC values observed in tractors equipped with Type B transmissions indicate that optimized gear ratios and reduced internal friction losses are essential for achieving improved fuel economy.

The interaction between engine and transmission systems further highlights the need for integrated powertrain optimization. Matching engine characteristics with appropriate transmission configurations can significantly enhance overall efficiency and reduce energy losses.

From a regulatory standpoint, current frameworks primarily focus on limiting pollutant emissions such as nitrogen oxides (NO_x) and particulate matter (PM), particularly under Stage V standards. However, these regulations do not directly address carbon dioxide (CO₂) emissions or fuel consumption.

This creates a critical gap, as demonstrated in this study, where significant differences in CO₂ emissions exist even among engines that fully comply with

current emission standards. Therefore, incorporating fuel efficiency indicators such as SFC or CO₂ emissions per unit of work into regulatory frameworks could provide a more comprehensive approach to environmental protection.

In addition, policy instruments such as financial incentives, tax reductions, or subsidy programs could be implemented to promote the adoption of high-efficiency tractor technologies. Such measures would accelerate the transition toward more sustainable agricultural practices.

At the national level, improving the average fuel efficiency of the tractor fleet would contribute not only to emission reduction targets but also to reducing dependency on fossil fuels and enhancing energy security.

8. CORRELATION BETWEEN ENGINE POWER AND SPECIFIC FUEL CONSUMPTION

An additional analysis was conducted to evaluate the relationship between rated engine power and specific fuel consumption.

The findings indicate that there is no strict linear relationship between engine power and SFC. Instead, fuel efficiency appears to depend more strongly on engine design characteristics than on absolute power output.

In general, smaller engines tend to operate closer to their optimal load conditions, which can result in relatively lower SFC values under certain operating conditions. However, larger engines may achieve higher efficiency when operating within their optimal load range, particularly in applications requiring sustained high-power output.

This observation suggests that engine sizing should be carefully matched to the intended application. Oversized engines operating under low load conditions may result in increased fuel consumption due to inefficient operating regimes. Conversely, undersized engines may experience excessive loading, leading to increased fuel consumption and potential durability issues.

Therefore, optimal tractor configuration requires a balance between engine power, load requirements, and operational conditions. Selecting an appropriately sized engine for the intended agricultural application is essential for maximizing fuel efficiency and minimizing environmental impact.

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CHAPTER 5

Generic Artificial Intelligence Synthetic Data Production in Agriculture

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Abstract

The rapid advancement of artificial intelligence (AI) technologies has significantly transformed data-driven sectors, including agriculture. In particular, generative artificial intelligence (GenAI) has emerged as a powerful tool for addressing data scarcity, improving model performance, and enhancing decision-making processes. This study examines the role and applications of generative AI in agriculture, with a specific focus on synthetic data generation techniques. First, the paper outlines the integration of AI into agricultural

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systems, highlighting its contributions to automation, efficiency, and resource optimization. It then explores key generative models, including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and diffusion models, and evaluates their effectiveness in producing high-quality synthetic datasets. These models enable the augmentation of limited or imbalanced datasets, improve disease detection accuracy, and support predictive modeling in areas such as crop management and yield estimation. Furthermore, synthetic data plays a crucial role in reducing dependency on costly and time-consuming field data collection processes. The findings suggest that generative AI not only enhances the performance of machine learning applications in agriculture but also facilitates broader accessibility to advanced technologies for farmers and decision-makers. As a result, these approaches contribute to sustainable agricultural practices by optimizing resource use and minimizing environmental impacts. The study concludes by emphasizing the importance of supporting the adoption of generative AI technologies through academic research and policy-driven initiatives.

1. Introduction

Nowadays, artificial intelligence is developing rapidly. With advancements in computing capacity and the widespread adoption of cloud technology, an increasing portion of the global economy has begun to benefit from artificial intelligence. Agriculture is one of the fields that is already beginning to see the benefits of artificial intelligence. Whether it's weed control, calculating the optimal time for crop harvesting, monitoring soil and crop health, or predicting yield in advance. AI (artificial intelligence) and ML (machine learning) have been tested as development tools in various industries over the past decade. However, it has only recently become clear that AI can be used to improve the agricultural decision-making process (Javaid et al., 2023). Especially in the agricultural sector, farmers are managing different planting stages, monitoring the health status of plants and the availability of nutrients, and optimizing yields at lower costs by utilizing AI applications and robotic technologies (e.g., unmanned aerial and ground vehicles); thus, they are saving on both labor and operational costs (Pallottino et al., 2025).

The increasing importance of generative artificial intelligence in various sectors has also brought the use of these technologies to the forefront in data-intensive fields such as agriculture and forestry. In this context, it becomes meaningful to examine the early applications of generative artificial intelligence in these fields. Today, agricultural and forestry activities are rapidly digitalizing; sensor technologies, remote sensing systems, and big data infrastructures are the fundamental components of this transformation. The large volumes

of data generated in this process can be used for quick decision-making thru real-time analysis as well as for comparative evaluations over time. At this point, Generative Artificial Intelligence models play an important role. These models accelerate data processing and analysis processes, enabling quicker output generation and contributing to rapid action based on these outputs. Additionally, these technologies partially reduce the level of technical expertise required in decision-making processes, allowing a broader user base to benefit from data-driven systems (Pallottino et al., 2025).

2. Generative Artificial Intelligence in Agriculture

Intelligent systems are divided into four categories: systems that think like humans, systems that act like humans, systems that think rationally, and systems that act rationally. These categories refer to thinking and behavior and evaluate their success in terms of fidelity to human performance or rationality. An artificial intelligence system can store and process data; it can also acquire, represent, and process information. Processing also includes the ability to derive new information from existing data (inference) (Oliveira and Silva, 2023).

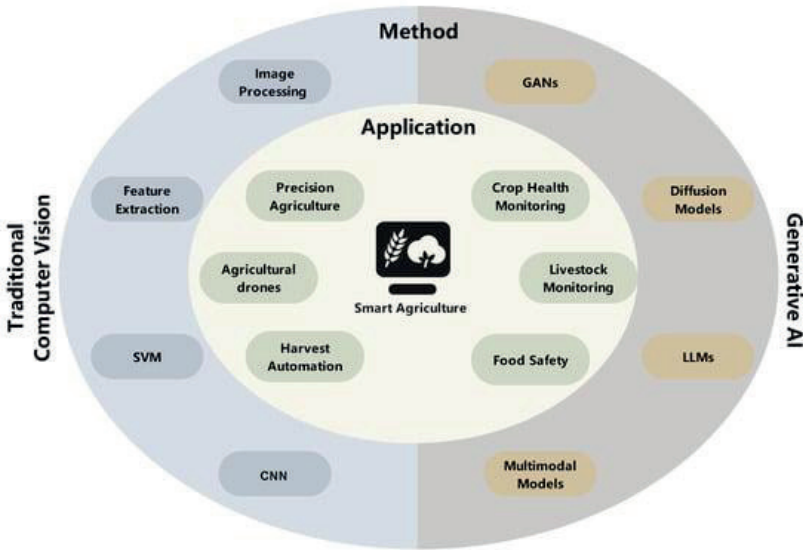


Figure 1. Overview of computer vision and generative artificial intelligence methods in smart agriculture applications (Min et al., 2025).

Figure 1 visually summarizes the methodological spectrum extending from traditional computer vision (CV) techniques to GenAI and highlights the key applications in the field of smart agriculture (Min et al., 2025). Generative

modeling is an artificial intelligence (AI) technique that produces synthetic content by analyzing training samples, learning their patterns and distributions, and then creating realistic copies. Generative AI (GAI) produces a wide range of content on a large scale by evaluating existing media such as text, graphics, sound, and video using generative modeling and advancements in deep learning (DL) (Jovanović and Campbell, 2022).

Most of the processes and steps involved in agriculture are manual. Artificial intelligence can assist with the most challenging and mundane tasks by enhancing existing technology. Agriculture is a labor-intensive sector, and labor shortages are common. Automation can help farmers solve this problem. Farmers can complete their tasks using various methods such as driverless tractors, smart irrigation and fertilization systems, intelligent spraying, vertical farming software, and AI-based harvesting robots. Agricultural machines driven by artificial intelligence are more efficient, productive, and faster than any human worker (Javaid et al., 2023).

3. Synthetic Data Generation in Agriculture

Early diagnosis of diseases in agricultural products allows for earlier interventions that can prevent their spread, significantly saving time and resources. Preventive measures are generally more effective when applied in the early stages of the disease; this leads to the use of fewer pesticides for pathogen control. Commercial agriculture currently relies on expert observers for disease detection. Ideally, observers should make daily rounds in the field, but due to costs and personnel limitations, these rounds are often much less frequent in practice. Manual detection methods are neither fast nor error-free – detecting symptoms in plants, especially in the early stages, requires attention and can sometimes lead to costly mistakes (Klein et al., 2024).

Synthetic data consists of artificially generated data. When data is scarce or of poor quality, synthetic data can be used, for example, to improve the performance of machine learning models (Figueira and Vaz, 2022).

3.1. GAN (Generative Adversarial Networks)

To address the issue of insufficient physical data, image augmentation can be used to expand and diversify datasets. Generative adversarial networks (GANs) offer an innovative approach to image augmentation by learning the underlying distributions of training data in a generative manner. This strategy is based on deep learning algorithms. The capacity of GANs to produce high-quality, balanced, and diverse synthetic images improves deep learning model training. GANs, in their most advanced variants, offer an effective way to

address issues such as data imbalance and diversity requirements, thereby enhancing model performance in agricultural processes (Rahman et al., 2024).

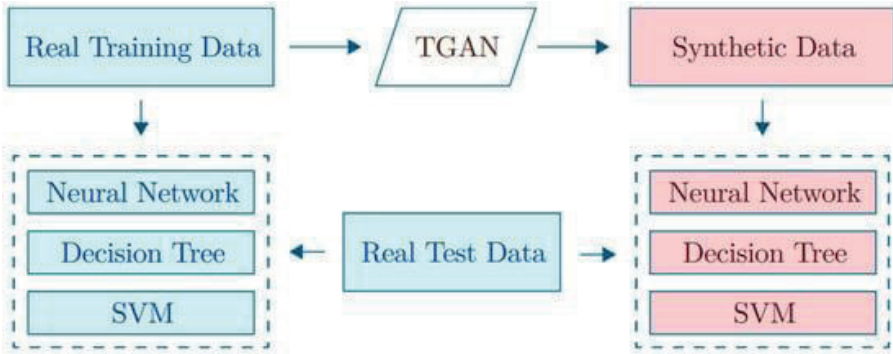


Figure 2. The process of training and evaluating a TGAN involves using real training data, including labels, to train the GAN and generate synthetic data. Using both real and synthetic data for multiple machine learning (Goyal et al., 2024).

As seen in Figure 2, it shows the training and evaluation process of TGAN. The average performance difference between the real and synthetic data produced using TGAN was 5.7%. This study demonstrates TGAN's ability to reliably generate synthetic data for data science applications and represents a significant advancement in relational database modeling (Goyal et al., 2024).

3.2. VAE (Variational Autoencoders)

VAEs are used in many areas of agriculture. VAEs are models that can learn the latent space representation of data, allowing them to capture the fundamental features and patterns in the input data. In the context of crop recommendation, VAEs can learn meaningful representations of various crop-related factors such as soil quality, climate conditions, and historical yield data. VAEs are generative models that can produce new data samples consistent with the learned data distribution. In crop recommendation, this capability can be used to create synthetic datasets that simulate various crop growth scenarios and conditions. These synthetic datasets can be valuable for training and evaluating recommendation models. VAEs are used for anomaly detection tasks in various fields. In the context of smart agriculture, VAEs can help identify unusual or abnormal conditions in field areas, such as diseases or pests, by detecting deviations from the learned data distribution.

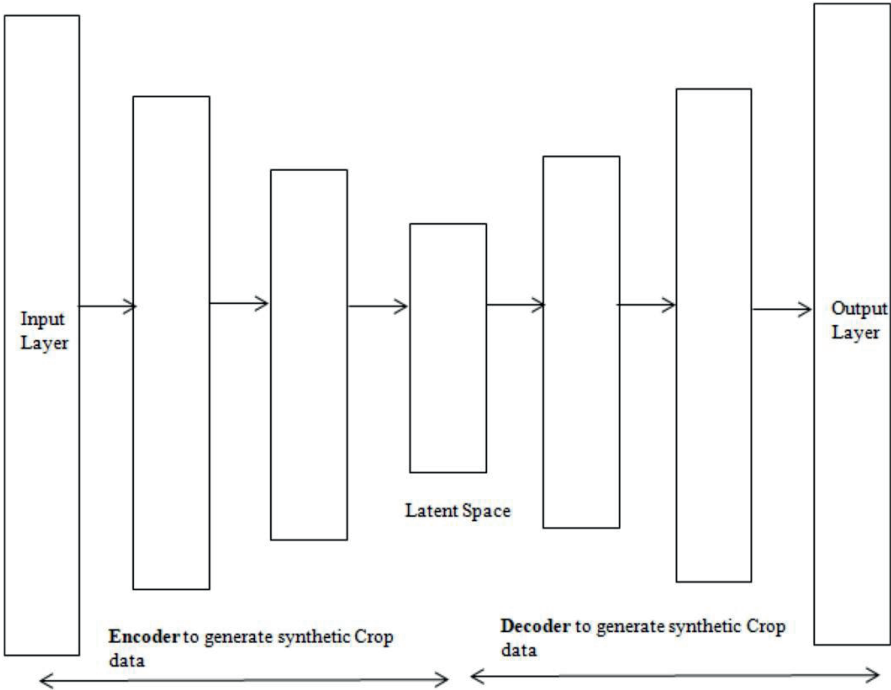


Figure 3. VAE architecture (Akkem et al., 2024)

VAEs can be used in multi-task learning scenarios, where they learn to generate data and simultaneously learn specific tasks related to crop recommendation, such as yield prediction or disease detection. This multi-task learning approach can enhance the overall performance of recommendation systems. VAEs can automatically extract relevant features from input data, thereby reducing the size of the dataset while preserving critical information. This feature extraction capability can simplify the recommendation process and improve the efficiency of recommendation algorithms from a Green Artificial Intelligence perspective. The effectiveness of VAEs, along with their ability to generate synthetic data, can support sustainable agriculture by optimizing resource use, reducing waste, and minimizing the environmental impacts of crop production. Although not directly related to crop recommendation, VAE are mentioned in the literature in the context of recommendation systems. VAEs can be adapted to create recommendation models for suggesting crop varieties or agricultural practices based on historical data and user preferences (Akkem et al., 2024).

3.3. Diffusion Models

Diffusion models, by training on a large number of data samples, not only generate images in the style of creative artists but also have the ability to produce new examples when very few training samples are available (Zhu J., 2024). The diffusion model is inspired by non-equilibrium thermodynamics (Sohl-Dickstein et al., 2015; Zhang et al., 2025) and the process begins by gradually adding noise to the input data along a Markov chain, continuing until it becomes completely pure, and then, starting from pure noise, it is returned to the real data through gradual noise removal. As a result, the diffusion model is trained more consistently than GAN (Zhang et al., 2025).

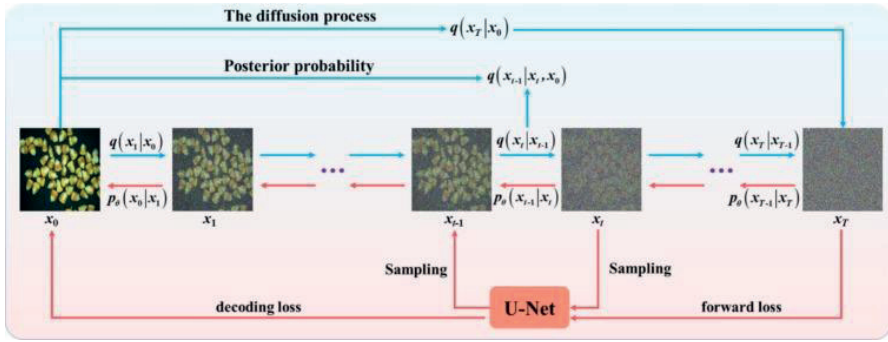


Figure 4 Forward noise addition and noise subtraction (Zhang et al., 2025)

As seen in Figure 4, diffusion models in agriculture can be classified as forward and reverse. The method proposed by diffusion not only surpasses traditional models in detection performance but also demonstrates high practicality, providing strong support for the smart and sustainable development of the industry (Yin et al., 2025).

4. Conclusion and Recommendations

With the rapid development of technology and the integration of artificial intelligence into agriculture, the diagnosis of diseases or pests under difficult conditions or those rarely seen is becoming simpler and more usable through features like data augmentation. The integration of generative models into decision support systems reduces the need for technical expertise, allowing farmers and decision-makers to benefit from big data more quickly and effectively. This situation provides cost optimization across a wide range, from reducing pesticide use to harvest scheduling. Producers should be supported in accessing this technology and being technically informed through both the academic community and government-supported projects.

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CHAPTER 6

Data Fusion in Agriculture: Integration of Satellite, UAV, and Sensor Data

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ABSTRACT

This study comprehensively examines the role and applications of data fusion in agriculture, focusing on the integration of satellite, unmanned aerial vehicle (UAV), and ground-based sensor data. The rapid digitalization of agricultural systems has led to the generation of large volumes of heterogeneous data characterized by differences in spatial, temporal, and spectral resolutions. In this context, data fusion emerges as a critical approach to combine multi-

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source data and enhance the accuracy, consistency, and reliability of agricultural analyses. The study presents the fundamental concepts of data fusion and categorizes fusion techniques into low-level, feature-level, and decision-level approaches. Furthermore, it evaluates major data sources used in agriculture, including satellite imagery for large-scale monitoring, UAV data for high-resolution observations, and IoT-based sensors for real-time environmental measurements. Various data fusion methods are discussed, including statistical approaches, machine learning-based techniques, and deep learning-based models, highlighting their advantages, limitations, and application potentials. The findings indicate that multi-source data fusion significantly improves applications such as crop monitoring, stress detection, yield prediction, and resource optimization within precision agriculture. Additionally, the integration of advanced artificial intelligence techniques enhances the capability of analyzing complex and high-dimensional datasets. However, challenges such as data standardization, interoperability, computational requirements, and user adaptation remain critical barriers. In conclusion, data fusion plays a pivotal role in advancing smart and sustainable agricultural systems by enabling more efficient resource management and informed decision-making processes. Future developments in artificial intelligence, IoT, and cloud-based systems are expected to further expand the applicability and impact of data fusion in Agriculture 4.0 and beyond.

1. INTRODUCTION

The process of digitalization in agriculture has not only been limited to the widespread use of data collection technologies but has also made it necessary to process this data in a holistic and meaningful manner (Nasirahmadi and Hensel, 2022; Gebresenbet et al., 2023). Data obtained from different sources such as satellite images, unmanned aerial vehicles (UAVs), and ground-based sensor systems show significant differences in terms of spatial resolution, temporal frequency, and spectral content (Omia et al., 2023; Bazrafkan et al., 2025). For example, while satellite data provides an advantage in monitoring large areas, UAVs offer higher spatial resolution; ground sensors produce micro-scale data with instantaneous and point measurements. This heterogeneous structure often renders analyzing based on a single data source insufficient.

In this context, data fusion emerges as a critical approach that enables the combination of information obtained from different data sources to achieve more consistent, accurate, and comprehensive results (Barbedo, 2022; Barrile et al., 2022; Saki et al., 2024). Data fusion encompasses low-level (raw data level), mid-level (feature level), and high-level (decision level) integration

techniques, with each level requiring different data processing strategies. Fusion at the raw data level involves the direct combination of data obtained from sensors, while at the feature level, the integration of extracted attributes is concerned. At the decision level, outputs obtained from different models are combined to create the final decision mechanism (Barbedo, 2022; Saki et al., 2024; Bazrafkan et al., 2025).

The application areas of data fusion in agriculture are quite extensive. Especially within the scope of precision agriculture, it provides significant contributions in areas such as plant health monitoring, stress detection, early warning systems for diseases and pests, yield prediction, and variable rate applications (Ouhami et al., 2021; Yang et al., 2025). For example, the combined evaluation of multispectral UAV images and data obtained from soil moisture sensors allows for more accurate detection of plants under water stress (Wang et al., 2024; Sharma et al., 2025). Similarly, the integration of satellite-based plant indices such as NDVI with meteorological data and soil properties enhances the accuracy of crop yield prediction models (Lekakis et al., 2022).

In recent years, the development of machine learning and especially deep learning-based approaches has significantly increased the effectiveness of data fusion (Zhao et al., 2024). Convolutional neural networks (CNN), recurrent neural networks (RNN), and transformer-based models have the capacity to process different types of data within the same model. In this way, both temporal and spatial dependencies can be analyzed more effectively. Additionally, thanks to multimodal learning approaches, image, sensor, and text-based data can be evaluated simultaneously, and more robust decision support systems can be developed (Gao et al., 2020; Li et al., 2024; Zhao et al., 2024). The theoretical framework and data flow process for multisource data fusion in agriculture are schematically presented in Figure 1.

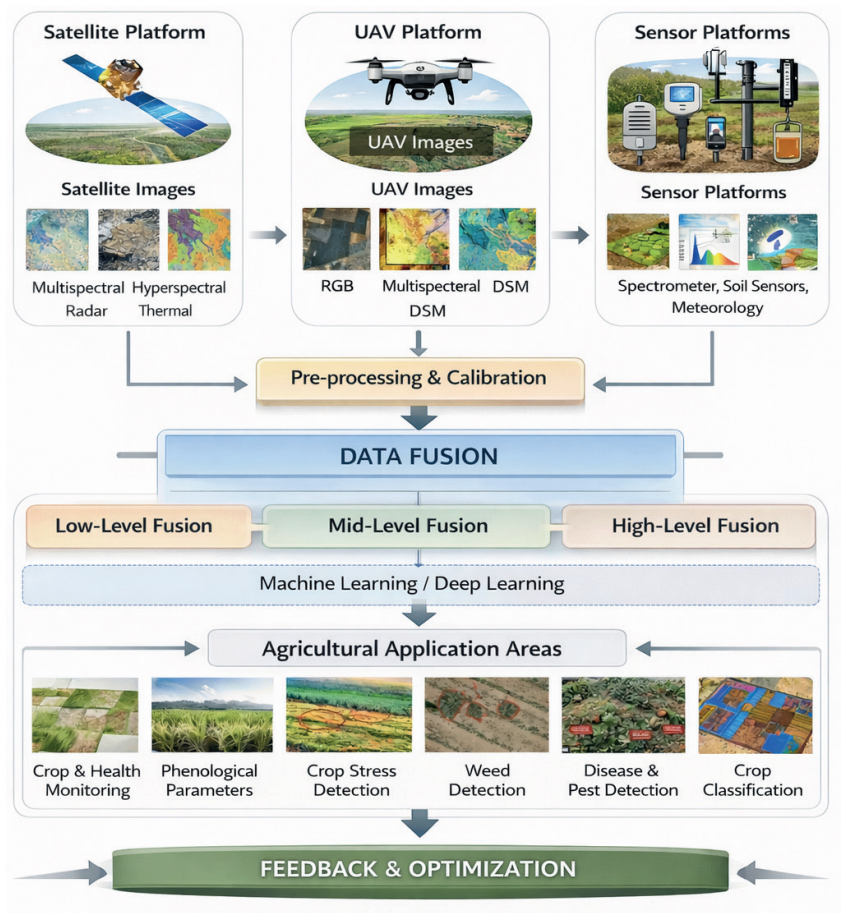


Figure 1. Multisource data fusion architecture and application areas in agriculture (developed from Allu and Mesapam, 2024).

Therefore, data fusion, as one of the fundamental components of digital transformation in agriculture, enables the synergistic use of different data sources and contributes to the development of more sustainable, efficient, and smart agricultural practices. In this section, the theoretical framework of data fusion and the fundamental methods used will be examined in detail, shedding light on future research directions.

2. THE CONCEPT AND TYPES OF DATA FUSION

2.1. What is Data Fusion?

Data fusion is defined as the process of combining, processing, and analyzing heterogeneous data obtained from different sensors, data sources, or measurement systems to enhance consistency, accuracy, and reliability (Barrile et al., 2022; Barbedo, 2022; Saki et al., 2024). This approach allows for the acquisition of more comprehensive and meaningful information at a level that a single data source cannot provide, thereby enhancing the effectiveness of decision support processes. Especially in digital agriculture applications, data fusion enables the evaluation of information obtained from satellite images, unmanned aerial vehicle (UAV) data, and ground-based sensors in a holistic manner, ensuring that processes such as monitoring plant health, yield prediction, and resource management are carried out more accurately and effectively (Maimaitijiang et al., 2020; Alexopoulos et al., 2023; Marzougui et al., 2023; Bazrafkan et al., 2025).

2.2. Fusion Levels

Data fusion is categorized into three basic levels—low, medium, and high—depending on the stage at which different data sources are combined. These levels are based on the integration of data at the raw data, feature, and decision levels. The conceptual framework for data fusion levels is shown in Figure 2.

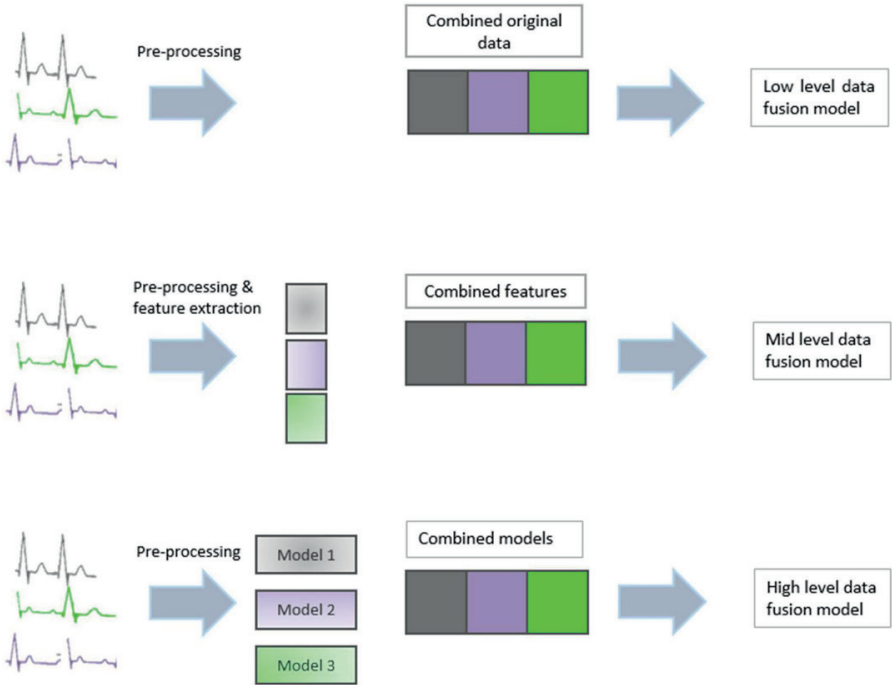


Figure 2. Data fusion levels (Hayes et al., 2023).

Low-Level Fusion

Low-level fusion is a data integration approach that involves directly combining raw data obtained from different sensors without any preprocessing, filtering, or feature extraction. In this method, data is integrated at the pixel or signal level, preserving the unique information contained in each data source and achieving a highly detailed data representation. Especially in the joint evaluation of satellite images, unmanned aerial vehicle (UAV) data, and ground-based sensor measurements, this approach is widely used, minimizing data loss and enabling precise analyses. However, due to the high volume of data, it requires significant storage and computational capacity, and it can also bring about alignment issues arising from the spatial and temporal resolution differences of different data sources (Krishnamurthi et al., 2020; Tao, 2024).

Feature-Level Fusion

Mid-level fusion is a data fusion approach that involves first extracting meaningful features from data obtained from different data sources and then integrating these features. In this method, instead of using raw data directly, distinctive features obtained from each data source are selected to create a

more compact and representative data structure. This approach, widely used in image processing, machine learning, and multi-sensor systems, reduces data size, lowers computational costs, and simultaneously ensures the preservation of important information. However, the success of the feature extraction process directly affects fusion performance, and if appropriate features are not selected, information loss may occur (Zhang et al., 2019; Ounoughi and Yahia, 2022).

Decision-Level Fusion

High-level fusion is a data fusion approach based on the combination of decision or classification outputs created because of independent analysis processes of information obtained from different data sources. In this method, each data source is processed with a separate model or algorithm, and the results obtained are integrated at the decision level. Using techniques such as voting, weighted averaging, or probabilistic methods, the final decision is formed, thereby leveraging the strengths of different models to achieve more robust and generalizable results. Especially widely used in machine learning and ensemble approaches, this method offers advantages of flexibility and interpretability, but its performance can vary depending on the consistency of the model outputs (Ballabio et al., 2019; Liu et al., 2022).

3. DATA SOURCES USED IN AGRICULTURE

3.1. Satellite Data

Satellite data stands out as an important data source in monitoring agricultural areas due to its advantage of covering large areas. These systems allow for the regular observation of agricultural lands on a regional and global scale, providing an effective monitoring capability, especially in large-scale production areas (Defourny et al., 2019). However, the temporal resolution of the data obtained from satellite systems can be relatively low, depending on their revisit times. Nevertheless, plant indices derived from satellite images, such as NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index), are widely and effectively used for assessing plant health, monitoring development processes, and identifying stress conditions (Radočaj et al., 2023; Atanasov et al., 2025).

3.2. UAV Data

Unmanned aerial vehicle (UAV) data offers a significant advantage in agricultural monitoring and analysis processes due to their high spatial resolution. These systems enable the visualization of agricultural fields in

much greater detail, making it possible to conduct evaluations at the plant level. Additionally, thanks to the flexible data collection capacity of UAVs, data can be obtained at any desired time and under any conditions, which allows for rapid and targeted observation, especially during critical growth periods. With these features, UAV data is effectively used in processes such as monitoring plant health and early detection of disease and stress symptoms in precision agriculture applications (Özgüven et al., 2022; Rejeb et al., 2022).

3.3. IoT and Sensor Data

IoT-based sensor systems are becoming an important data source by offering real-time and continuous monitoring capabilities in agricultural production processes (Alahmad et al., 2023; Mansoor et al., 2025). Through these systems, critical environmental parameters such as soil moisture, temperature, pH, and nutrient status can be monitored with high temporal and spatial resolution, and data is transmitted to cloud platforms via wireless networks (Alahmad et al., 2023; Pechlivani et al., 2023). The advantage of continuous monitoring allows for the dynamic tracking of factors affecting plant growth, rapid detection of sudden changes, and timely irrigation, fertilization, and other interventions (Ali et al., 2023; Mansoor et al., 2025). Thus, IoT and sensor data provide significant contributions to optimizing water and fertilizer use, saving labor and energy, and increasing efficiency in precision agriculture applications.

4. DATA FUSION METHODS

4.1. Statistical Methods

Statistical methods are data fusion approaches based on the integration of information obtained from different data sources through mathematical and probabilistic models (Alofi et al., 2017). The aim of these methods is to evaluate the information coming from sensors or different data sets in accordance with their statistical relationships, thereby obtaining more reliable and consistent results (Jaradat et al., 2022).

Regression analysis and Bayesian approaches are widely used for the probabilistic modeling of data from multiple sensors and the quantification of uncertainty; for example, Bayesian dynamic regression and Gaussian process regression enhance the prediction accuracy of missing or noisy data by utilizing inter-sensor correlations (Martino et al., 2020). The Kalman filter and its derivatives are fundamental tools for the fusion of multiple sensor data in dynamic systems, especially those involving noise, and they enhance the

accuracy of state estimation in applications such as navigation, positioning, and environmental monitoring (Priyanka et al., 2024).

However, these methods are strongly dependent on model assumptions (e.g., linearity, Gaussian noise, constant covariance); data quality, the reliability level of the sources, and the selection of the appropriate model/kernel/filter directly affect fusion performance (Jaradat et al., 2022). Inclusion of data sources with incorrect assumptions or faulty quality into the fusion can lead to increased prediction errors and inconsistent results (Jaradat et al., 2022; Li, 2024).

4.2. Machine Learning-Based Fusion

Machine learning-based fusion is defined as a data fusion approach that relies on the integration of information obtained from different data sources through learning algorithms (Meng et al., 2020). In this method, data obtained from sensors or different platforms are analyzed by the model to learn the complex and nonlinear relationships between them, and higher accuracy predictions or classifications are made. Algorithms such as support vector machines, decision trees, random forests, and artificial neural networks are widely used, especially in the joint evaluation of multidimensional and heterogeneous datasets (Meng et al., 2020; Saim and Aly, 2025). This approach, while offering high generalization capability and flexibility, also includes limitations such as the requirement for large and high-quality data for model training and sensitivity to hyperparameter optimization (Zhang et al., 2019; Ounoughi and Yahia, 2022).

4.3. Deep Learning-Based Fusion

Deep learning-based fusion is an advanced data fusion approach that relies on the automatic learning and integration of information obtained from different data sources through deep neural networks (Zhao et al., 2024). In this method, hybrid models that use architectures such as CNN (Convolutional Neural Networks) and LSTM (Long Short-Term Memory) together can simultaneously analyze both spatial and temporal features (Yang et al., 2021). Additionally, through multi-input models, different types of data such as satellite, UAV, and sensor data can be processed within the same network structure, providing more comprehensive and robust representation learning (Li et al., 2022). Deep learning-based fusion offers high accuracy and automatic feature extraction advantages in complex and high-dimensional datasets, but it also has disadvantages such as large data requirements, high computational costs, and limited model interpretability (Zhang et al., 2019; Liu et al., 2022).

5. CONCLUSION AND RECOMMENDATIONS

The integrated collection, processing, and analysis of data obtained from different remote sensing systems and ground-based sensors have become one of the fundamental building blocks of smart and sustainable agricultural systems. The integration of multi-resolution and multi-temporal data obtained from satellites, unmanned aerial vehicles (UAVs), and IoT-based sensor networks through data fusion approaches enables the more precise and accurate monitoring of crop development status, soil properties, water stress, and nutrient element requirements. This integrated analysis capacity reduces costs and increases yield and profitability by ensuring that agricultural inputs (water, fertilizer, pesticide, etc.) are used at optimal levels. At the same time, it supports environmental sustainability by contributing to the widespread adoption of precision agriculture practices, significantly reducing soil and water pollution caused by excessive input usage.

In the near future, it is anticipated that decision support systems based on multi-source data fusion will be used more widely and effectively due to advancements in artificial intelligence, deep learning, and big data analytics. It is expected that these systems will improve decision-making processes by providing producers with real-time, location-specific, and dynamic recommendations. IoT-based sensor networks and autonomous agricultural machines, integrated with cloud and edge computing technologies, will accelerate the transition to Agriculture 4.0 and Agriculture 5.0 by synchronizing data collection, analysis, and application processes. Additionally, thanks to digital twin technologies and simulation-based approaches, it will become possible to pre-model agricultural production processes and minimize risks.

However, there are some structural and technical barriers to the effective and widespread use of these technologies. The inability to achieve data standardization, interoperability issues between different platforms, high-cost infrastructure requirements, and the management of large volumes of data are among the significant challenges. Additionally, the adaptation of farmers and agricultural stakeholders to digital technologies, the lack of technical knowledge, and the need for training are also critical factors that need to be considered. In this context, the development of legal regulations for data security and privacy, the establishment of open data standards, and the design of user-friendly systems are of great importance.

In conclusion, in order for smart agriculture applications based on data fusion to be disseminated sustainably and effectively, it is necessary to increase interdisciplinary research, strengthen public-private sector collaborations,

expand farmer training programs, and develop appropriate policy tools. The steps taken in this direction will both support the increase in agricultural production efficiency and contribute to the conservation of natural resources, making it possible to achieve sustainable agriculture goals.

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CHAPTER 7

Intelligent Dairy Cattle Decision Support System Using NLP and Metaheuristic Optimization

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Abstract

This study proposes an innovative hybrid decision support system that integrates Natural Language Processing (NLP) and metaheuristic optimization techniques to enhance productivity, economic efficiency, and animal welfare in intelligent dairy cattle systems. While traditional approaches mainly rely on structured numerical data obtained from IoT sensors, this study also incorporates unstructured textual data derived from field observations and technical evaluations of animal nutrition experts into the model. In the proposed system, expert opinions are analyzed using NLP techniques and transformed into numerical parameters to generate dynamic constraints for metaheuristic algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Through this structure, the model can adapt to real-time conditions and incorporate biological and managerial factors into the decision-making process that are often overlooked in conventional optimization approaches. The model

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was evaluated through a ration optimization scenario, and it was observed that NLP-based constraints had a significant impact on feed composition and decision outputs. The results demonstrate that the proposed approach not only reduces feed costs but also increases milk yield and enables early detection of potential health risks, thereby providing a proactive management mechanism.

In conclusion, the integration of human expertise with AI-based optimization offers significant contributions to the development of more flexible, adaptive, and context-aware decision support systems in precision livestock farming.

Keywords: Intelligent Dairy Farming, Natural Language Processing, Metaheuristic Optimization, Decision Support Systems, Animal Nutrition

1. Introduction

The projected increase in the global population and the corresponding rise in demand for animal protein sources have made it necessary to improve productivity in the agriculture and livestock sectors. According to United Nations projections, the global population is expected to reach approximately 9.7 billion by 2050, making sustainable productivity growth in milk and meat production a strategic necessity (FAO, 2017). However, traditional livestock production methods are insufficient to meet this growing demand due to factors such as rising feed costs, labor constraints, the impacts of climate change, and the limited availability of natural resources. In this context, digitalization and data-driven management approaches are playing an increasingly critical role in the livestock sector (Wolfert et al., 2017).

At the core of this transformation is the concept of Precision Livestock Farming (PLF), which integrates technologies such as the Internet of Things (IoT), big data analytics, and Artificial Intelligence (AI), leading to significant structural changes in dairy farming operations (Berckmans, 2017). PLF systems aim to enhance production efficiency and improve animal welfare by continuously monitoring physiological and behavioral parameters of animals in real time and enabling early warning systems and automated decision-making mechanisms (Banhazi et al., 2012). In particular, continuous monitoring of parameters such as milk yield, rumination time, activity level, and feed intake allows for more precise and timely interventions in farm management.

Smart dairy farm management requires the simultaneous evaluation of multidimensional and interdependent processes such as animal health, milk production, reproductive performance, and feeding strategies. However, data collected from the field is not limited to sensor-based numerical information. Textual data such as veterinarians' notes, caretaker observation reports,

nutritionists' evaluations, and historical records also play a critical role in decision-making processes. These unstructured data are often overlooked or not effectively utilized by traditional data analysis methods.

At this point, Natural Language Processing (NLP) techniques emerge as a powerful tool for analyzing text-based data and transforming them into meaningful and usable information. Through NLP methods, qualitative data such as expert opinions, field observations, and clinical notes can be quantified and integrated into decision support systems (Kamilaris et al., 2018). With the advancement of transformer-based models, the extraction of contextual meaning from textual data has significantly improved (Devlin et al., 2019; Trapanese et al., 2025). This development enables moving beyond systems that rely solely on sensor data, allowing for the creation of more comprehensive and context-aware decision-making mechanisms.

On the other hand, the large-scale and multidimensional data generated by intelligent systems bring about complex optimization problems in areas such as ration formulation, labor planning, production optimization, and disease management. These problems are typically multi-objective, non-linear, and high-dimensional in nature. Traditional deterministic optimization methods often fall short in addressing such challenges (Tedeschi et al., 2005). In this regard, metaheuristic optimization algorithms stand out as powerful tools capable of providing effective solutions in complex search spaces (Kennedy & Eberhart, 1995; Storn & Price, 1997).

This study proposes an innovative intelligent decision support system architecture that integrates NLP-based data enrichment with metaheuristic optimization techniques. The proposed approach goes beyond conventional systems that rely solely on numerical data by incorporating human expertise and field experience into the decision-making process. In this respect, the study aims to contribute to the development of next-generation decision support systems in smart livestock farming, emphasizing human–technology integration.

2. Theoretical Framework and Algorithms of Metaheuristic Optimization

Optimization is the process of finding the best value of an objective function (e.g., cost minimization or productivity maximization) under given constraints. Agricultural and livestock systems, particularly dairy farming, are complex structures in which numerous variables (such as feed composition, animal health, and environmental factors) must be evaluated simultaneously. In such systems, classical derivative-based optimization methods (e.g., Linear

Programming) are often insufficient due to nonlinearity, high dimensionality, and uncertainty inherent in the problem (Nocedal & Wright, 2006).

In this context, metaheuristic optimization algorithms have emerged as powerful alternatives capable of finding near-optimal solutions within acceptable time frames in large and complex search spaces (Blum & Roli, 2003). Although metaheuristic methods do not guarantee exact optimal solutions, they provide effective and practical approaches, especially for NP-hard problems.

2.1. Fundamental Principles of Metaheuristic Algorithms

The success of metaheuristic algorithms relies on the balanced use of two fundamental search strategies:

- *Exploration (Diversification):*

This strategy enables the search of different and previously unexplored regions of the solution space, increasing the likelihood of escaping local optima and reaching the global optimum (Yang, 2010).

- *Exploitation (Intensification):*

This strategy focuses on refining and improving already promising solutions by searching in their vicinity (Blum & Roli, 2003).

The balance between these two mechanisms is the most critical factor affecting algorithm performance. Excessive exploration leads to slow convergence, whereas excessive exploitation increases the risk of being trapped in local optima.

Metaheuristic algorithms are generally inspired by natural processes. Evolutionary mechanisms (Genetic Algorithms), swarm behaviors (PSO), collective intelligence (ACO), and physical processes (Simulated Annealing) constitute the main sources of inspiration for these approaches (Yang, 2010).

2.2. Main Algorithms Used in Dairy Cattle Decision Support Systems

In smart livestock applications, metaheuristic algorithms are widely used, particularly for solving multi-objective optimization problems (Herrera et al., 2016; Deb, 2001). The main algorithms highlighted in this study are described below.

2.2.1. Genetic Algorithms (GA)

Genetic Algorithms are based on Darwin's theory of natural selection. Solutions are represented as "*chromosomes*" and evolved within a population through iterative processes (Goldberg, 1989).

- *Mechanism*: New generations are created using selection, crossover, and mutation operators.
- *Advantage*: Strong performance in complex and non-linear problems.
- *Application Area*: Ration optimization, feed cost reduction, and production planning in dairy farming.

2.2.2. Particle Swarm Optimization (PSO)

PSO is inspired by the collective movement behavior of bird flocks. Each candidate solution (particle) moves by considering both its own best experience and the best solution found by the swarm (Kennedy & Eberhart, 1995).

- *Advantage*: Requires few parameters and exhibits fast convergence.
- *Application Area*: Parameter optimization in productivity prediction models and sensor data analysis.

2.2.3. Ant Colony Optimization (ACO)

ACO is based on the behavior of ants using pheromone trails to find the shortest path (Dorigo & Gambardella, 1997).

- *Advantage*: High performance in combinatorial optimization problems.
- *Application Area*: Logistics planning, milk collection routing, and distribution optimization.

2.2.4. Differential Evolution (DE)

Differential Evolution is a powerful algorithm developed for continuous optimization problems (Storn & Price, 1997).

- *Advantage*: Simple structure and high solution quality.
- *Application Area*: Parameter tuning and model calibration in milk yield prediction models.

2.3. The Necessity of Metaheuristic Approaches in Smart Dairy Farming

Dairy farming is a system that requires real-time decision-making involving multiple criteria. For instance, even a small change in feed ration can significantly affect milk yield, animal health, and economic cost (Beever, 2006).

Metaheuristic algorithms provide the following advantages in such complex systems:

- *Cost optimization:* Minimization of feed costs
- *Health management:* Reduction of mastitis and metabolic disease risks
- *Quality optimization:* Maximization of milk components (fat, protein)

In this context, metaheuristic approaches offer effective solutions for multi-objective optimization problems, enabling the simultaneous optimization of conflicting objectives (Deb, 2001; Usigbe et al., 2025).

In conclusion, metaheuristic algorithms provide both flexibility and computational efficiency in intelligent dairy cattle decision support systems, offering a more practical and robust solution approach compared to traditional methods.

3. Utilization of NLP Techniques in Dairy Cattle Datasets

Decision support systems (DSS) in smart dairy farming have traditionally focused on numerical data generated by IoT sensors, such as milk yield, rumination temperature, and activity levels (Wathes et al., 2008). However, a significant amount of information vital to farm management is stored in the form of “unstructured text.” This includes field notes from animal nutritionists, feed quality assessment records, commentaries on ration adjustments, and periodic health logs.

NLP enables the conversion of this verbal data into machine-processable numerical vectors, transforming qualitative observations into powerful features for metaheuristic optimization models (Jurafsky & Martin, 2023). NLP technology provides the opportunity to digitalize professional field experience and integrate it directly into automated decision-making processes.

3.1. Sources of Unstructured Textual Data

In the dairy cattle ecosystem, NLP fills the information gaps that quantitative data cannot explain. The primary data sources include:

- *Expert Field Notes and Observation Reports*: Free-text observations from nutritionists or caretakers regarding appetite, manure scores, gait abnormalities (lameness), or estrus behavior.
- *Clinical and Treatment Records*: Diagnoses, medication dosages, and responses to treatment. These records contain constraints that directly influence the nutritional requirements of the animal (Wang et al., 2021).
- *Academic Decision Rules and Literature*: Utilizing NLP to scan scientific literature and feeding protocols to incorporate up-to-date knowledge bases into the system (Miner et al., 2012).

3.2. Text Preprocessing: From Raw Text to Smart Data

To transform textual data into inputs for metaheuristic optimization algorithms, several preprocessing stages are required:

1. **Tokenization**: Breaking the text down into words or sub-word units.
2. **Lemmatization/Stemming**: Reducing words to their root form to ensure semantic consistency (e.g., mapping “milked” and “milking” to the core context of “milk”).
3. **Stop-words Removal**: Cleaning out high-frequency words with low informational value (e.g., “and”, “with”, “for”).
4. **Vectorization**: Representing words in a mathematical space. While traditional techniques like TF-IDF are used, modern models such as Word2Vec or transformer-based BERT (Bidirectional Encoder Representations from Transformers) are preferred for capturing deep contextual meaning (Devlin et al., 2019).

3.3. Specialized NLP Tasks for Dairy Farming

In the proposed system, NLP feeds the optimization engine by performing the following specific tasks:

- *Named Entity Recognition (NER)*: Automatically identifying cow ear-tag numbers, specific feed ingredients, medication names, and disease types (e.g., Mastitis, Ketosis) within the text (Lample et al., 2016).

- **Sentiment and Status Analysis:** Semantically extracting the general welfare and health status (good/poor/critical) from descriptors in the text.
- **Topic Modeling:** Automatically clustering and identifying chronic issues on the farm, such as “feed refusal” or “metabolic disorders,” from thousands of expert notes (Blei et al., 2003; Trapanese et al., 2025).

3.4. Integration of NLP and Decision Support Mechanisms

The true value of the NLP module emerges when its outputs serve as inputs for metaheuristic algorithms. A “*health score*” or “*anomaly detection*” derived from text analysis is assigned as a **constraint** or a component of the **objective function** within the optimization process.

For instance, an animal nutritionist’s note mentioning “mild loss of appetite” is converted by the system into a weight coefficient. This information instantly updates the energy requirement coefficient of the respective animal during a **Genetic Algorithm (GA)** based ration optimization, triggering a shift from a purely cost-oriented ration to a health-oriented one.

This integration ensures the system encompasses not only “*what is happening*” (numerical data) but also “*how it is interpreted*” by experts (textual experience), resulting in a more intelligent, proactive, and explainable decision-making structure (Tecuci, 2012).

4. Architecture of an NLP and Metaheuristic-Integrated Intelligent Decision Support System

This section presents an intelligent decision support system (DSS) architecture in which qualitative observations from animal nutrition experts and quantitative data obtained from IoT sensors are processed in an integrated manner, and optimal feeding strategies are generated through metaheuristic algorithms (Cabrera et al., 2019; Niloofar et al., 2021; Tedeschi, Greenwood & Halachmi, 2021; Akintan, Gebremedhin & Uyeh, 2025). The proposed structure adopts a hybrid approach that is both data-driven and supported by expert knowledge, and it consists of four main layers (Power, 2002).

4.1. Data Acquisition Layer (Sensor and Text Input)

This layer constitutes the primary data source of the system and includes two main types of data:

1. **Structured Data (Numerical Data):** These include parameters such as milk yield, milk components, daily feed intake, rumination time, and animal activity data obtained through IoT sensors and farm management systems (Cabrera et al., 2019; Tedeschi et al., 2021; Hu et al., 2023; Tangorra et al., 2024). In smart dairy farming and Precision Livestock Farming (PLF) applications, the continuous collection and management of such multi-source sensor data within large data streams are considered fundamental components (Tedeschi, Greenwood & Halachmi, 2021).
2. **Unstructured Data (Textual Data):** These consist of field notes recorded by animal nutrition experts. Examples include:
 - o “Feed particle size is not appropriate”
 - o “Manure score decreased from 3 to 2”
 - o “Signs of acidosis observed in animals”
 - o “The dry matter content of the new silage batch appears low”

Such textual data reveal conditions that cannot be fully explained by numerical sensor data alone, thereby enhancing the contextual awareness of the system (Ferris, Christensen & Wangen, 2020; Niloofar et al., 2021; Rao & Neethirajan, 2025).

4.2. NLP Analysis Module (Quantification of Expert Knowledge)

The notes provided by animal nutrition experts are analyzed by the NLP module, which extracts semantic labels and numerical constraints related to nutrition, health, and behavior from unstructured observations (Ferris, et al., 2020; Rao & Neethirajan, 2025; Ferreira & Dórea, 2025). Recent studies demonstrate that large language models and modern NLP techniques are highly effective in extracting diagnostic and management-related labels from textual sources such as veterinary records, feeding logs, and farmer observations, particularly within digital twin and decision support architectures for dairy farming (Ferris et al., 2020).

Through this process, qualitative expert knowledge is transformed into quantitative inputs that can be utilized by optimization algorithms (Niloofar et al., 2021; Akintan et al., 2025). For example, when an expert notes that

“*rumination time has decreased in cows,*” the NLP system translates this statement into numerical constraints such as “*Rumination_Alert = 1*” and “*Fiber_Requirement_Increase = 15%*.” In this way, qualitative, experience-based knowledge is systematically converted into machine-interpretable quantitative parameters.

4.3. Metaheuristic Optimization Engine (Decision-Making Core)

This layer functions as the “*brain*” of the system. Expert-derived constraints from the NLP module are combined with performance data from the IoT layer, and optimization is performed using metaheuristic methods such as Genetic Algorithms (GA), multi-objective GA, or Particle Swarm Optimization (PSO). These methods simultaneously optimize objectives such as feed cost, milk yield, milk quality, and environmental impact (Niloofar et al., 2021; Akintan et al., 2025; Usigbe et al., 2025).

In digital twin-based dairy nutrition architectures, multi-objective genetic algorithms have been successfully applied to optimize both feed composition and greenhouse gas emissions. Similarly, in smart agriculture, metaheuristic and operations research techniques are widely integrated into decision support systems to balance economic and environmental objectives, such as optimizing feed and fertilizer ratios.

The optimization process typically includes:

- *Objective Function:* Achieving maximum milk yield with minimum feed cost (multi-objective optimization).
- *Constraints:* Animal live weight, lactation stage, and specific health or condition limits defined by the animal nutrition expert.

5. System Flow Diagram and Application Scenario

In this section, the integrated operation of the NLP and metaheuristic components described theoretically is modeled through a system flow and illustrated with a realistic livestock farming scenario (Tedeschi et al., 2021; Niloofar et al., 2021; Campos et al., 2023; Rao & Neethirajan, 2025; Ferreira & Dórea, 2025).

5.1. System Flow Diagram (Algorithmic Process)

The operational logic of the system follows the hierarchical steps below:

1. Input Layer:

- o *Sensor Data*: Daily milk yield, activity score, rumination time
- o *Expert Text Input*: Notes from animal nutrition experts (in free-text format)

2. NLP Processing Layer:

- o Text preprocessing (stop-word removal, lemmatization)
- o Vectorization (e.g., BERT-based analysis)
- o Constraint extraction (e.g., deriving the rule *“increase fiber ratio by 5%”* from the statement *“manure consistency is soft”*)

3. Optimization Layer (Metaheuristic Engine):

- o Integration of NLP-derived constraints with numerical data into the objective function
- o Selection of the most cost-effective and healthiest feed ration among thousands of alternatives using Genetic Algorithms (GA) or Particle Swarm Optimization (PSO)

4. Output Layer:

- o Revised ration formulation
- o Early warning notifications

5.2. Example Application Scenario: Seasonal Silage Change and Acidosis Risk

A realistic scenario designed to evaluate the system is presented below:

Situation: A newly opened batch of corn silage in a dairy farm is suspected to have fermentation issues.

- **Step 1 (Observation):** The animal nutrition expert observes that some cows are selectively eating and that manure scores have decreased. The following note is entered into the system: *“The newly opened silage appears to have high acidity. Mild loss of appetite and soft manure have been observed in cows. It may be necessary to rebalance the forage ratio in the ration.”*
- **Step 2 (NLP Analysis):** The NLP module analyzes the text and detects keywords such as *“high acidity”* and *“soft manure.”* It assigns the label *“Acidosis Risk = High”* and generates new constraints for the optimization algorithm: *“Decrease starch ratio by 2% and increase effective fiber (peNDF) by 3%.”*

- **Step 3 (Metaheuristic Optimization):** The Genetic Algorithm evaluates available feed resources (alfalfa, straw, concentrate feed, etc.) and computes a new ration that satisfies both the health-related constraints derived from NLP and production targets, while minimizing cost. This process is completed within seconds.
- **Step 4 (Outcome):** The system sends the following notification to the farm manager: *“Based on the animal nutrition expert’s note, an acidosis risk has been detected. The ration has been updated from formula r01 to r02 (high-fiber formulation). Estimated daily cost increase: 0.45 TL per animal.”*

5.3. Strategic Advantages of the System

As demonstrated in this scenario, if only sensor data had been considered, the system might not have responded until a decline in milk yield occurred (approximately 2–3 days later). However, the integration of the animal nutrition expert’s experience into the system through NLP enabled the problem to be addressed proactively, before any productivity loss was observed. The metaheuristic optimization component, in turn, managed this sudden change in the most rational and cost-effective manner. Recent studies applying text mining and topic modeling in dairy farming have demonstrated the potential of extracting actionable insights from large-scale textual datasets (Trapanese et al., 2025).

6. Conclusion and Future Work

In this book chapter, an innovative decision support system architecture that integrates NLP and metaheuristic optimization techniques has been proposed to address the complex management and feeding challenges faced by modern dairy farming systems. The study demonstrates that digitalization in the livestock sector should not rely solely on numerical data obtained from sensors but must also incorporate human expertise and domain knowledge into the system.

6.1. Key Contributions and Evaluation

Based on the analyses conducted and the designed scenarios, the following key conclusions have been reached:

- *Integration of Qualitative and Quantitative Data:* The use of NLP techniques enables the incorporation of field observations and technical notes from animal nutrition experts into the system. This allows for the early detection of anomalies and risks (e.g., acidosis, feed sorting,

changes in manure score) that cannot be identified through numerical data alone.

- *Optimization Flexibility:* Metaheuristic algorithms (GA, PSO, ACO) are capable of providing near-global optimal solutions within seconds in environments characterized by multiple criteria and dynamic constraints, such as dairy farming. This capability is critical for minimizing feed costs and ensuring sustainable milk production.
- **Proactive Decision-Making Mechanism:** Rather than operating as a reactive system that responds only after problems occur, the proposed approach enables proactive management by utilizing expert insights to intervene before productivity losses arise.

6.2. Future Work and Recommendations

To further advance research in this field, the following key directions are proposed:

- *Integration of Large Language Models (LLMs):* Future studies may benefit from replacing conventional NLP techniques with advanced large language models such as GPT or LLaMA. These models can more effectively interpret complex and semantically rich reports generated by animal nutrition experts, leading to improved decision-making accuracy.
- *Hybrid Models with Computer Vision:* Incorporating image processing modules into the NLP and optimization framework—such as systems capable of automatically detecting body condition scores (BCS) or lameness—can significantly enhance the accuracy and robustness of the overall system.
- *Real-Time Edge Computing Implementation:* Deploying computationally intensive metaheuristic algorithms on local farm-based servers (edge computing), rather than relying solely on cloud infrastructure, can ensure continuous and reliable decision support, even in the case of internet disruptions.

In conclusion, intelligent dairy farming systems enriched with NLP and optimized through metaheuristic approaches are strong candidates to become one of the foundational pillars of the future *Smart Farm* paradigm. This hybrid approach has the potential to enhance animal welfare while maximizing farm profitability, thereby making a strategic contribution to global food security.

This chapter not only reviews existing studies but also proposes a novel hybrid decision support framework integrating NLP and metaheuristic optimization techniques for smart dairy farming systems.

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